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Synergistic effect of lean practices on lead time reduction: mediating role of manufacturing flexibility

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Received 11 May 2019
Revised 30 September 2019
24 November 2019
Accepted 14 March 2020

Abstract

Purpose – This study scrutinized the synergistic effects of lean manufacturing (LM) on lead time reduction (LR) while investigating the mediating role of manufacturing flexibility (MF) in that relationship within the context of batch and mass customization manufacturers.

Design/methodology/approach – This cross-sectional survey involved 160 large batch and mass customization manufacturers in Indonesia. Data were analyzed by using the PLS path modeling approach and multigroup analysis.

Findings – The positive synergistic direct effects of LM on LR and MF were revealed in both process types. In mass customization, MF mediates the effect of LM on LR. However, such a mediating effect was not found in the batch process due to the insignificant effect of MF on LR.

Practical implications – The findings offered theoretical and practical insights supporting the manufacturers to grasp potential benefits through the holistic LM implementation as well as the suitable strategies to improve MF and reduce lead time by considering the types of the production process.

Originality/value – This study bridged the gaps regarding the comparison of LM implementation and its influence on MF and LR in mass customization and batch production.

Keywords Lean manufacturing, Flexibility, Lead time, Complementarity, Contingency, PLS-MGA

Paper type Research paper

Introduction

In today's globally competitive market, the top priority of businesses is to satisfy customers. The higher the customer satisfaction, the higher their loyalty, which subsequently could increase their purchases. To stay competitive, companies should produce at lower costs without compromising quality. On top of that, manufacturers should deliver their products quickly on a timely basis, which positively drives customer satisfaction, sales performance, and financial objectives (Nawanir *et al.*, 2016). As the heterogeneity of customer demand is inevitable in today's volatile markets (Metternich *et al.*, 2013; Wei *et al.*, 2017), manufacturers are challenged to supply product varieties in a short period. It hints that companies must be flexible, adaptable, agile, and highly responsive to customer needs (Wei *et al.*, 2017).

The authors would like to acknowledge manufacturing companies in Indonesia who have participated in this study. We are also grateful to the anonymous reviewers of the journal for their extremely useful suggestions to improve the quality of the article.

Benchmarking: An International Journal
Vol. 27 No. 5, 2020
pp. 1815-1842

1463-5771
DOI 10.1108/BIJ-05-2019-0205

To increase the adaptability to the ever-changing demand while shortening lead time, a manufacturer should increase its flexibility (Al-Zu'bi, 2015), which is in line with the main objectives of LM (Hallgren and Olhager, 2009). Manufacturing flexibility (MF) refers to the capability of a manufacturing system to adapt to external and internal changes, yet continue to produce a variety of products and volumes without compromising performance (Swamidass, 2000). Specifically, MF is characterized by quick response to customer demand (Boyle and Scherrer-Rathje, 2009), because of higher ability to adjust to the changes in product design/model (product mix flexibility), volume (volume flexibility), and routing (routing flexibility) (Rogers *et al.*, 2011); besides the flexibility in work assignment to production workers (worker flexibility) (Mendes and Machado, 2015) and machines (machines flexibility) (Rogers *et al.*, 2011). These characteristics potentially reduce lead time. However, the strategies of how manufacturers achieve the appropriate levels of MF in facing environmental uncertainty are still questionable, besides the studies on the implication of LM on MF are still limited (Phan *et al.*, 2019). Few studies engaged in LM practices and MF. Bhamu and Sangwan (2014) and Chauhan and Singh (2013) revealed that manufacturers could gain benefits from LM implementation in terms of workers and machines' flexibility. Thus, the manufacturers are flexible in terms of assigning jobs to workers and machines. Dal Pont *et al.* (2008) found a significant effect of LM on product mix and volume flexibilities. Besides the studies relating LM with MF, several studies have also linked LM with LR. Uhrin *et al.* (2017), dos Santos Bento and Tontini (2018), Panwar *et al.* (2017), Nawanir *et al.* (2013), and Matsui (2007) suggested a positive linkage between LM and LR.

Even though few investigations have connected LM with MF and LR, little efforts have been made to link the three variables and to investigate how a contextual factor (i.e. types of the manufacturing process) influences the implementation of LM as well as its effects on MF and LR. The consideration of the contextual factor is crucial because the application of manufacturing practices depends on plants' characteristics (Shah and Ward, 2003). Manufacturers adopting different processes tend to implement LM in different ways (Panwar *et al.*, 2017). In such a way, every manufacturer may implement a different set of LM practices and activities. Consequently, the contributions of the LM on performance among manufacturers tend to be diverse. This diversity is possibly due to some contingency factors like types of the manufacturing process. Noticeably, consideration of types of the process still lacks in the recent literature. Therefore, this study endeavors at scrutinizing synergistic effects of LM on LR in the context of batch and mass customization processes, while investigating the mediating role of MF in that relationship. This study bridges the gap of the inconsistent impact of LM on MF and LR while serving in-depth insights for academicians and industry executives into the holistic implementation of LM as well as examining its impact on MF and LR contingent to types of the manufacturing process.

This paper consists of seven sections. After the brief introduction, the second section provides a literature review and hypotheses development. The third section explains the research methodology. Subsequently, the results obtained from the structural equation modeling (SEM) analysis will be presented in the fourth section, highlighting the synergistic effect of LM on MF and LR in different manufacturing processes. The following sections are a discussion on the empirical results and implications of the study. Lastly, limitations and suggestions for future studies are drawn.

Literature review and hypotheses development

Lean manufacturing and practices

Originated from the shop floors of Toyota Motor Corporation in the late 1950s to early 1960s, Toyota Production System (TPS) received much attention throughout the globe. As an Americanized version of TPS, Krafcik (1988) invented the term "lean" to articulate a manufacturing system that expends fewer resources with extraordinary performance. In line with TPS, LM focuses on doing more with fewer resources (Balzer *et al.*, 2015) while targeting flexibility, quality, productivity, customer satisfaction, profitability, lead time, costs, and inventory. Nowadays, LM is acknowledged as a gold standard of the modern manufacturing system.

Through an in-depth review of the literature, this study generated a bundle of LM practices. Conceptual and empirical studies were referred to develop the bundle of practices by considering their significant effects on organizational performance (see Table 1). In selecting the practices, common practices from previous studies were compiled in a spreadsheet. They were then regrouped based on their similarities into nine practices, which are cellular layouts (CL), flexible resources (FR), pull system (PS), uniform production level (UPL), quick setup (QS), small-lot production (SLP), total productive maintenance (TPM), quality control (QC), and supplier networks (SN). Even though this study did not comprise some of the practices discussed in previous studies as separated components, many were incorporated into related practices.

Complementarity concept of LM. LM was commonly conceptualized as a combination of practices, which corroborate with each other to target waste elimination. Few studies, such as Khanchanapong *et al.* (2014), Furlan *et al.* (2011b), Nawanir *et al.* (2018b), Ghobakhloo and Azar (2018), and Shah and Ward (2003), emphasized the complementarity among the practices suggesting simultaneous adoption. The simultaneous implementation could considerably contribute to firms' performance because of inter-connectivity among the practices (Furlan *et al.*, 2011a; Nawanir *et al.*, 2018a). In short, this mutually supportive relationships tended to support the notion that the synergistic effect of LM helps manufacturers to leverage performance to a greater height.

Literature	FR	CL	PS	SLP	QS	UPL	QC	TPM	SN
Hallgren and Olhager (2009)		*	*			*			
Zelbst *et al.* (2010)	*		*	*	*	*	*	*	
Phan and Matsui (2010)	*	*	*		*	*	*	*	*
Bonavia and Marin-Garcia (2011)		*	*		*	*	*	*	
Inman *et al.* (2011)	*	*	*		*	*	*	*	*
Furlan *et al.* (2011a, b)	*	*	*	*	*	*	*		*
Eswaramoorthi *et al.* (2011)	*	*	*	*	*	*	*	*	*
Panizzolo *et al.* (2012)	*	*	*	*	*	*	*	*	*
Vinodh and Joy (2012)	*	*			*	*	*		*
Marodin and Saurin (2013)	*	*	*	*	*	*	*	*	*
Khanchanapong *et al.* (2014)	*	*	*		*	*	*		*
Kull *et al.* (2014)		*	*		*		*	*	
Belekoukias *et al.* (2014)	*	*	*	*	*	*	*	*	*
Sharma *et al.* (2015)		*	*		*	*	*	*	*
Chavez *et al.* (2015)			*		*				*
Godinho Filho *et al.* (2016)	*	*	*		*		*	*	*
Cherrafi *et al.* (2016)		*	*		*		*	*	*
Zahraee (2016)		*	*		*		*	*	
Uhrin *et al.* (2017)		*	*				*	*	
Panwar *et al.* (2017)	*		*	*	*	*	*	*	*
EL-Khalil (2018)	*				*	*	*	*	
Yadav *et al.* (2019)			*		*	*	*	*	*
Sahoo and Yadav (2018)							*	*	*
Solke and Singh (2018)	*		*				*		
dos Santos Bento and Tontini (2018)	*		*		*	*	*	*	*
Bai *et al.* (2019)	*	*	*	*	*	*	*	*	*
Tortorella *et al.* (2018)	*		*			*	*	*	*

Note(s): *It indicates that the lean practices are discussed in the literature

Table 1.
LM practices in recent literature

The findings from the previous studies are in line with the theory of complementarity invented by Edgeworth (1881), which was popularized by Milgrom and Roberts (1990, 1995). The theory highlighted that isolated practices are powerless to achieve outstanding performance. Hence, the practices should be adopted holistically, by which one practice may enhance the contributions of others and *vice-versa*. However, the complementarity among the practices depends on the fitness between the practices. As pointed out by Venkatraman and Prescott (1990), a good fit among the practices would lead to higher benefits on organizations. Therefore, the concept affords the foundation to comprehend how various practices corroborate with each other through the explanation of how they contribute to organizational performance and competitiveness. The theory and findings in previous studies provide strong support to model LM as a second-order construct consisting of nine LM practices as first-order constructs. Thus, the following is hypothesized:

H1. LM is a second-order construct, whereby LM practices have strong positive correlations with each other.

The synergistic effect of LM on MF. The adoption of LM leads to high MF (Al-Zu'bi, 2015; Lucherini and Rapaccini, 2017; Metternich *et al.*, 2013; Nawanir *et al.*, 2013). For instance, LM promotes producing in small lot size (Furlan *et al.*, 2011a), which is supported by quick setups of machines and equipment. Through these practices, a production line becomes more flexible in terms of product mix. LM also encourages to utilize multi-purpose machines and equipment (Nawanir *et al.*, 2018a), which can perform several functions. When one machine fails, other machines can execute similar jobs. Along with this, multi-skilled workers who can handle several different jobs are also demanded in an LM system (Khanchanapong *et al.*, 2014). Consequently, a work assignment for workers becomes more flexible. If a workplace has no demand, workers can be assigned to other workplaces (Ketokivi and Schroeder, 2004).

On top of that, if a worker is away, other workers can do the same tasks. Besides, the use of manufacturing cells in cellular layouts also supports MF. With that, the arrangement of production flow can be adjusted in case of machine failure, the layout of workstations can be converted to fit the required manufacturing process, and equipment can easily be moved from one place to another (Nawanir *et al.*, 2018b; Rogers *et al.*, 2011). In other words, routing flexibility could be enhanced. Moreover, strong supplier networks leverage supply flexibility, especially when demand is increasing. Through a partnership with suppliers, demand fluctuations can be tackled and volume flexibility can be increased without incurring extra-cost and lowering performance (Khanchanapong *et al.*, 2014; Matsui, 2007). This may also support the new-product launch and modifications of the existing products (Boyle and Scherrer-Rathje, 2009). Accordingly, the adoption of all LM practices would synergistically improve MF, which leads to the following hypothesis.

H2. There is a positive relationship between the second-order construct of LM and MF.

The synergistic effect of LM on LR. Lead time can take on different meanings depending on the range of activities included in its interpretation. It may apply to particular operations, individually or collectively. Following Gaither and Frazier (2002), the lead time is defined as the amount of time to get the materials in from suppliers, to produce all parts and assemblies, and to deliver to customers. In line with that, Christiansen *et al.* (2003) classified lead times into three categories; purchasing, manufacturing, and delivery lead times. Purchasing lead time refers to the time between placing an order to a supplier and receiving purchased items from the supplier (Jayaram and Vickery, 1998). Manufacturing lead time indicates the time taken in the production line from its first entrance until its completion (Singh *et al.*, 2010). Delivery lead time signifies the time taken by finished goods to get delivered to customers (Angelis *et al.*, 2011; Rogers, 2008). As most of the LM practices are implemented on the shop floor, assessing its impact on components of manufacturing lead time is essential. This study divides lead time into four categories; setup, processing, moving, and waiting times. Setup time is defined as the time to prepare equipment, materials and workstations for an operation (Fullerton and Wempe, 2009; Zahraee, 2016). Processing time refers to the times for productive operations (Gaither and Frazier, 2002), waiting time is the time for a part to be moved to the subsequent operation (Tersine, 1994), and moving time is transportation time from one storage to another, or between workstations (Cheng and Podolsky, 1993).

LM reduces lead times (dos Santos Bento and Tontini, 2018; Fullerton and Wempe, 2009; Hofer *et al.*, 2012; Singh *et al.*, 2010) because one of the targeted performances of LM implementation is to speed up production processes, while increasing its efficiency (Khanchanapong *et al.*, 2014). In an LM system, production and material movements are authorized by *kanban* through the implementation of the pull system, which are performed just as needed, in the right quality, right quantity (neither too much nor too little), right time (neither too early nor too late) and precisely where required based on customer demand (Forrester *et al.*, 2010). Supported by producing in small lot sizes, the pull system eliminates inventory (e.g. raw materials, work in process (WIP), and finished goods), which subsequently speeds up process flows (Chen and Tan, 2011). Anand and Kodali (2009) stated that shorter lead time could be achieved through the uniform production level through workload balancing, standardize processes, and mixed-model assembly. More importantly, as the LM system promotes quick setup through the principle of the single minute of exchange dies (SMED), internal setup time can be reduced by converting most of them to external setups (Moxham and Greatbanks, 2001). Also, through the collaborative networks with suppliers, purchasing lead time can be reduced as the suppliers could react quickly to respond to the fluctuation of demand (Khanchanapong *et al.*, 2014), besides their ability to deliver materials in a just-in-time basis (Matsui, 2007). Other practices, such as flexible resources, cellular layouts, TPM and quality control through quality at the source and *poka-yoke*, make sense to contribute to LR. Several studies support this opinion, such as Fullerton and McWatters (2001), Shah and Ward (2003) and Matsui (2007), who had confirmed the positive linkage between LM and LR. Based on the argument and evidence provided earlier, the following hypothesis is formulated:

H3. There is a positive relationship between the second-order construct of LM and LR.

The effect of MF on LR. Indeed, the more flexible the production line, the shorter the lead time (Inman *et al.*, 2011; Qrunfeh and Tarafdar, 2013). MF may reduce lead times in several ways. For example, a flexible production line is characterized by the quick response to changes in demand (Solke and Singh, 2018), not only in terms of product mix (designs and model) but also in production volume (Boyle and Scherrer-Rathje, 2009). It could be supported by quick setups and the use of flexible machines, equipment, tools, jigs and fixtures (Rogers *et al.*, 2011), which consequently shortens setup and waiting times. More importantly, flexibility in work assignments to machines and workers may also reduce processing and moving times (Rogers *et al.*, 2011; Rogers, 2008), because of the ability of machines and workers to perform multiple jobs and operations. Multi-skilled workers could augment their ability to familiarize themselves with the whole production process, and therefore, it facilitates and expedites the new product development process (Mendes and Machado, 2015). To a greater extent, as the machines and workers are flexible, the production lines should have a high ability to adjust to changes in production routing in case of machine breakdown and other production disruption. Several studies highlighted the positive impact of MF on LR (Mendes and Machado, 2015; Rogers *et al.*, 2011; Rogers, 2008; Wei *et al.*, 2017). Based on the above discussions, this study hypothesizes the following:

H4. There is a positive relationship between MF and LR.

Indirect effect of LM on LR. Based on the facts, figures, and arguments provided in the development of hypotheses 2, 3, and 4, there are strong supports that holistic implementation of LM may affect LR directly and indirectly. Indirectly, the LM tends to improve MF in the initial stage (Agus and Hajinoor, 2012; Bhamu and Sangwan, 2014; Chauhan and Singh, 2013; Mackelprang and Nair, 2010), and subsequently the improvement on MF will reduce lead time (Mendes and Machado, 2015; Rogers *et al.*, 2011; Rogers, 2008; Wei *et al.*, 2017). Given that, the following is hypothesized:

H5. The second-order construct of LM has a positive indirect effect on LR through MF as a mediating variable.

Contingent effect of types of the production process. Besides the complementarity theory, contingency theory (Lawrence and Lorsch, 1967a, b) also supports the relationships between the variables of this study. The theory says that the implementation of any practices is contingent on organizational characteristics (Lawrence and Lorsch, 1967b). In other words, the practices must fit their context, while different organizations have different characteristics. It is where the concept of fit comes in. Specifically, the theory puts LM practices in a pragmatic point of view rather than arguing that the practices are an ideal approach with universal applications. It also tends to suggest that LM practices are not a sophisticated method with multiple capabilities, which can work in all situations. It seems common-sense that the adoption of LM and their impacts on performance might be contingent on some contextual variables. This perspective is in line with Cua *et al.* (2001), Shah and Ward (2003), and Tortorella *et al.* (2018), who stated that LM practices should be tailored to suit a particular manufacturing context and environment.

It is well-known that LM applies to all types of industries (White and Prybutok, 2001). However, the implementation of practices should match with factory characteristics (Cua *et al.*, 2001), including the type of manufacturing process, which was considered as an influential factor in the adoption of manufacturing practices (including LM), the extent of the practices implementation and definitely, its effects on the desired achievement. This study focuses on the implementation of LM and its impact on MF and LR in mass customization and batch manufacturing system.

The batch manufacturing system is characterized by producing semi-standardized products in medium volume (Fogarty *et al.*, 1991). Moderately large batches of the same product are processed once or repetitively. Thus, it requires multi-functional machines and equipment with special jigs and fixtures. In this process, the products from one functionally specialized workstation are pushed to its subsequent workstation in large quantities per batch (Todorova and Dugger, 2015), regardless of whether it is ready to receive or not. Consequently, the jobs may be queued up in some workstations, and it causes bottlenecks and excess work-in-process. As the queue time is longer and work-in-process is high, several issues may negatively affect the manufacturing system in terms of lower flexibility, longer lead time and scheduling problem.

Mass customization represents a manufacturing process, which focuses on producing high varieties of products in high volumes. It refers to the capability to manufacture and provide varieties of customized products that meet the specific needs of individual customers through a flexible process in high volumes (Da Silveira *et al.*, 2001; Sandrin *et al.*, 2018). In this process, even though the product is manufactured in a wide variety and volume, the quality, cost, and delivery performance are comparable to mass production (Murat Kristal *et al.*, 2010). The fluctuation in customer demand inspired the raising of this production paradigm in terms of variation of products, quality, price, and delivery. This is coherent with a postulation from Wang *et al.* (2016) signifying four aspects of mass customization capability: (1) customizing products while maintaining high volume, (2) customizing products without considerably increasing costs, (3) quick response to customization demands and

(4) customizing products with consistent quality. To achieve these capabilities, MF is one of the critical requirements (Suzić *et al.*, 2018). Therefore, supported with contingency theory, the following hypothesis was posited.

H6. The relationships between variables differ significantly due to different characteristics between two groups (i.e., batch and mass customization).

Methodology

Measurement development

This cross-sectional survey used a questionnaire to collect primary data. The questionnaire was developed through a collaborative process, starting from an extensive review of literature in LM, MF and FR. The first section of the questionnaire (adopted from Nawanir *et al.* (2018b)) is aimed to gain information regarding the implementation of LM practices. The second section depicted measurements of MF and LR to the improvement achieved by the companies during the last five years. MF was measured by using five indicators (adapted from Rogers (2008)), with six indicators of lead time (adapted from several sources, such as Fullerton and Wempe (2009), Stevenson (2012) and Heizer and Render (2011)). In both sections, the respondents were requested to answer on an interval scale from 1 (strongly disagree) to 6 (strongly agree). The use of this scale was rationalized by Krosnick (1991) to prevent respondents from answering an ambiguous response, besides to reduce social desirability bias of answering at a neutral point. Finally, the last section depicts the respondent profiles.

An initial draft of the questionnaire was pre-tested through a series of the review process by five scholars in the field to ensure content validity, simplicity, clarity, and understandability of the measurement. Subsequently, the improved draft was sent to practitioners from five large discrete process manufacturers to clarify the comprehensiveness and clarity of the questionnaire. Their feedbacks were then used for further improvement.

Sample and data collection

The data were collected from large manufacturers in Indonesia, which were selected randomly based on the directory provided by the Indonesian Central Bureau of Statistics. The selected companies were first telephoned to confirm their formal addresses while ensuring their qualifications. This step is vital as this study focuses on large manufacturers applying mass customization or batch production only. A total of 500 questionnaires was sent to top and middle management (e.g. production manager, head of the production department, and production director) of the qualified companies. Follow-up contacts with non-response companies were made to ensure a reasonably acceptable response rate. A total of 160 completed booklets were returned, generating a 32% effective response rate. The respondents consist of 92 companies implementing batch and 68 adopting mass customization. This response rate is acceptable when dealing with middle and top management in manufacturing industries (Latan *et al.*, 2018). An independent sample *t*-test indicated that no significant difference between early and late responses; therefore non-response bias is not an issue in this study. Table 2 summaries the demographic data of the respondents.

Findings

The data was mainly analyzed with PLS path modeling using SmartPLS 3.2.8. The primary considerations of selecting this technique are: 1) SEM is superior features over the regressions in terms of its simultaneous estimation of all parameters in a model (Iacobucci *et al.*, 2007), 2) PLS-SEM enables researchers to conduct group segmentation through partial least square-multigroup analysis (PLS-MGA) (Henseler, 2012; Matthews, 2017), and 3) PLS-SEM is able to provide more complete information regarding the extent to which the model is

	Batch		Mass customization		Total	
	Count	%	Count	%	Count	%
Industry						
Electronics and instrumentation	8	5.00%	6	3.75%	14	8.75%
Furniture, wood products and plaiting materials	27	16.88%	6	3.75%	33	20.63%
Machinery and equipment	15	9.38%	13	8.13%	28	17.50%
Textile, tanning, and dressing of leather	35	21.88%	32	20.00%	67	41.88%
Vehicles and transport equipment	7	4.38%	11	6.88%	18	11.25%
Job title						
Head of operation/production department	21	13.13%	14	8.75%	35	21.88%
Production director	9	5.63%	7	4.38%	16	10.00%
Production manager	57	35.63%	44	27.50%	101	63.13%
Other middle management positions in production	5	3.13%	3	1.88%	8	5.00%
Number of employees						
100–300	26	16.25%	11	6.88%	37	23.13%
More than 300	66	41.25%	57	35.63%	123	76.88%
Years working in the company						
3–5 years	19	11.88%	14	8.75%	33	20.63%
More than 5 years	73	45.63%	54	33.75%	127	79.38%
Years working in the current position						
1–3 years	37	23.13%	31	19.38%	68	42.50%
Less than 1 year	11	6.88%	6	3.75%	17	10.63%
More than 3 years	44	27.50%	31	19.38%	75	46.88%
Grand Total	92	57.50%	68	42.50%	160	100.00%

Table 2.
Demographic data of respondents

supported by data, such as goodness of fit measures and predictive relevance (Hair *et al.*, 2017; Latan *et al.*, 2018). This study used a consistent estimator through the application of consistent PLS (PLSc) because of the confirmatory nature of this study. As in CB-SEM, this estimator provides the consistent model estimates that disattenuate the correlations between pairs of latent variables (Dijkstra and Henseler, 2015). In general, data analysis follows the following stages. First, the measurement model was assessed to ensure construct validity. Second, the assessment of the structural model was done for hypotheses testing. Finally, a multigroup analysis (PLS-MGA) using a permutation procedure was applied to compare invariance and path coefficients between the two groups of sub-sample.

Construct validity. Convergent validity, composite reliability, and discriminant validity were used to assess the construct validity. Outer loadings and average variance extracted (AVE) indicate convergent validity. The outer loading for each item should be higher than 0.7, and the AVE of each construct should be above 0.5. However, the outer loading of 0.5 is still acceptable as long as AVE for the particular construct meets the requirement of 0.5 (Hair *et al.*, 2017). The AVE of less than 0.5 indicates that the items fail to explain most of the variance of the construct. Besides the convergent validity, composite reliability (CR) representing the internal consistency of indicators in measuring a construct was also assessed. The CR of 0.7 indicates sufficient internal consistency (Hair *et al.*, 2017). A repeated indicator approach was applied to assess the second-order construct of LM. This approach uses all items of first-order constructs measuring the second-order construct as a combined aggregate indicator for that second-order construct (Hair *et al.*, 2017). The assessment results for both batch and mass customization presented in Table 3 confirm that convergent validity and CR requirement are met for all first and second-order constructs.

Discriminant validity was assessed by using the Heterotrait-Monotrait Ratio of Correlation (HTMT). This advanced measure is superior in terms of methodological robustness compared to the criterion of Fornell and Larcker (1981) and cross-loading, besides this approach can overcome limitations in the previous measures (Henseler *et al.*, 2015). Table 4 shows that all the HTMT values are less than the threshold value of 0.90. Thus, there are no discriminant validity issues for measurement models.

Two criteria were used to test the first hypothesis; outer loadings of all the first-order constructs (each of LM practices) on the second-order construct (see Table 3) and correlation coefficients among the practices as presented in Table 5. For the samples implementing the batch process, the outer loadings of first-order constructs range between 0.591 and 0.893, with 59% AVE of second-order construct LM, whereas for mass customization, the loadings range from 0.640 to 0.890 with 62% variance explained in the second-order construct LM. Also, the correlations coefficients among the LM practices range between 0.345 and 0.861 (batch), and between 0.340 and 0.873 (mass customization), which the majority of them are higher than 0.5, which according to Cohen (1988) represent strong associations and interdependency. Based on these criteria, hypothesis 1 stating that LM practices are complementary with each other tends to be supported for both batch and mass customization.

Common method variance. Common methods variance (CMV) might be introduced in research due to a single informant data source (Podsakoff *et al.*, 2003), which may influence the associations among the variables measured by using the same method (MacKenzie and Podsakoff, 2012). According to Kline (2011), the presence of CMV in a model is indicated by the inability of the model to achieve discriminant validity. The poor discriminant validity indicates that all the manifest variables measure only one domain. This study also assessed CMV by using the technique suggested by Kock (2015). As addressed by Kock (2015), a VIF value greater than 3.3 projected a sign of pathological collinearity, and also as a symptom that a model may be affected by CMV. The assessment using SmartPLS 3 suggested that this research is free of the CMV issue as all the inner VIF values are less than 3.3 for both mass customization and batch processes.

Structural model assessment. After conforming construct validity and reliability, the next stage is aimed at assessing the structural model and testing hypotheses. By using the two-stage approach, goodness-of-fit measures were first assessed for both processes. SRMR value described the discrepancy between the observed correlations, and the model-implied correlations should be less than or equal to 0.08 (Hair *et al.*, 2014). NFI measuring the χ^2 value of the proposed model relative to the χ^2 value of the null model should be more than 0.9 (Hu and Bentler, 1998). SRMR values of 0.068 and 0.071 were obtained for batch and mass customization, respectively. Therefore, the assessment of the two structural models suggests an adequate fit.

Before going ahead with hypotheses' testing, the study assessed whether or not the multicollinearity is an issue in the structural model. The presence of multicollinearity is likely to confound the individual effect of exogenous variables on the endogenous variable (Hair *et al.*, 2017). Variance inflation factor (VIF) of less than 3.3 specifies the absence of multicollinearity. Table 6 shows that there is no multicollinearity issue in the structural model. Furthermore, the structural model was evaluated by scrutinizing the coefficient of determination (R^2 or adjusted R^2) and effect size (f^2) through consistent PLS algorithm procedure (Dijkstra and Henseler, 2015). R^2 indicates the contributions of all exogenous variables on an endogenous variable, inferring the total variance in an endogenous variable that can be explained by exogenous variables. As a rule of thumb stated by Hair *et al.* (2017), the R^2 values 0.75, 0.50, and 0.25 reflect substantial, moderate, and weak contributions of exogenous variables on an endogenous variable, respectively. Based on the analysis results exhibited in Table 6, in companies implementing batch, 66.10% variance in MF is explained by LM, and LM explains 65.70% variance in LR as the effect of MF on LR is insignificant. On

Construct	Item code	Item	Batch Loading	AVE	CR	Mass customization Loading	AVE	CR
CL	CL1	Machines are close to each other	0.823	0.692	0.918	0.774	0.713	0.925
	CL2	The layout of workstations can easily be changed depending on the sequence of operations required	0.859			0.854		
	CL3	Families of products determine our factory layout	0.766			0.747		
	CL4	Machines can easily be moved from one workstation to another	0.838			0.962		
	CL5	We group different equipment into a workstation to process a family of parts with similar requirements	0.872			0.867		
FR	FR1	When one machine is broken down, different types of machine can be used to perform the same jobs	0.800	0.681	0.894	0.717	0.631	0.871
	FR2	If one production worker is absent, another worker can perform the same responsibilities	0.858			0.697		
	FR3	We use general-purpose machines, which can perform several essential functions	0.711			0.872		
	FR4	When one machine is stopped, production workers are not idle	0.919			0.875		
PS	PS1	Kanban system is used to authorize production	0.904	0.745	0.921	0.857	0.787	0.936
	PS2	Production at a workstation is performed based on the demand of its subsequent workstation	0.835			0.962		
	PS3	We produce an item only when requested by its users	0.773			0.908		
	PS4	We use a kanban system to authorize material movements	0.931			0.816		
QC	QC1	We use statistical techniques to reduce process variances	0.857	0.702	0.934	0.775	0.650	0.918
	QC2	We use visual control systems as a mechanism to make problems visible	0.810			0.849		
	QC3	Production processes on production floors are monitored with statistical quality control techniques	0.805			0.772		
	QC4	Quality problems can be traced to their source easily	0.810			0.813		
	QC5	Production workers can identify quality problems easily	0.876			0.817		
	QC6	Production workers are authorized to stop production if serious quality problems occur	0.865			0.810		
QS	QS1	We converted most of the machine setups to external setup that can be performed while the machine is running	0.783	0.581	0.847	0.726	0.620	0.867
	QS2	Production workers perform their own machines' setups	0.769			0.800		
	QS3	We aggressively work on reducing machines' setup times	0.729			0.792		
	QS4	We can quickly perform our machines' setup if there is a change in process requirements	0.768			0.827		
SLP	SLP1	We produce more frequent but smaller lot size	0.923	0.745	0.920	0.897	0.780	0.934
	SLP2	We emphasize producing a small number of items together in a batch	0.818			0.922		
	SLP3	We strictly avoid the flow of one type of item in large quantity together	0.973			0.832		
	SLP4	We emphasize producing in small lot sizes to increase manufacturing flexibility	0.716			0.878		
SN	SN1	Our suppliers deliver materials to us just as it is needed (on a just-in-time basis)	0.855	0.719	0.927	0.788	0.724	0.929
	SN2	We strive to establish long-term relationships with suppliers	0.864			0.891		
	SN3	We emphasize to work together with suppliers for mutual benefits	0.821			0.878		
	SN4	We rely on a small number of high-performance suppliers	0.889			0.845		
	SN5	Development programs are provided to suppliers	0.808			0.850		
TPM	TPM1	We ensure that machines are in a high state of readiness for production at all the time	0.859	0.735	0.933	0.891	0.649	0.902
	TPM2	We dedicate periodic inspection to keep machines in operation	0.843			0.803		
	TPM3	We have a sound system of daily maintenance to prevent machine breakdowns from occurring	0.882			0.767		
	TPM4	We scrupulously clean workspaces to make unusual occurrences noticeable	0.839			0.852		
	TPM5	We have time reserved each day for maintenance activities	0.862			0.701		

(*continued*)

Table 3.
Convergent validity and composite reliability assessment results

Construct	Item code	Item	Batch Loading	AVE	CR	Mass customization Loading	AVE	CR
UPL	UPL1	We produce more than one product model from day to day (mixed model production)	0.898	0.661	0.906	0.949	0.611	0.884
	UPL2	We emphasize a more accurate forecast to reduce variability in production	0.767			0.735		
	UPL3	Each product is produced in a relatively fixed quantity per production period	0.675			0.650		
	UPL4	We emphasize to equate workloads in each production process	0.808			0.892		
	UPL5	Daily production of different product models is arranged in the same ratio with monthly demand	0.895			0.628		
LR	LR1	Times it takes for products to get through the factory have reduced	0.704	0.677	0.912	0.777	0.746	0.936
	LR2	Machine setup times have reduced	0.773			0.899		
	LR3	Transportation times of an item between workstations have reduced	0.923			0.884		
	LR4	Waiting times for an item to be moved to the next operation have reduced	0.868			0.863		
	LR5	Times required to move the finished goods from our plant to customers have reduced	0.829			0.890		
MF	MF1	Ability to adjust to changes in product design/model by customer demand has improved	0.735	0.634	0.896	0.824	0.715	0.926
	MF2	Ability to adjust to changes in production volume by customer demand has improved	0.834			0.782		
	MF3	Ability to adjust to changes in production routing in case of machine breakdown has improved	0.869			0.889		
	MF4	Flexibility in work assignments to production workers has improved	0.782			0.923		
	MF5	Flexibility in work assignments to machines has improved	0.751			0.801		
LM*	CL	Cellular Layouts	0.794	0.663	0.946	0.861	0.692	0.952
	FR	Flexible Resources	0.835			0.693		
	PS	Pull System	0.712			0.873		
	QC	Quality Control	0.893			0.942		
	QS	Quick Setups	0.890			0.864		
	SLP	Small Lots Production	0.621			0.668		
	SN	Supplier Networks	0.827			0.839		
	TPM	Total Productive Maintenance	0.938			0.911		
	UPL	Uniform Production Level	0.769			0.794		

Note(s): *Second order construct

Table 3.

	CL	FR	LR	MF	PS	QC	QS	SLP	SN	TPM	UPL
CL	–	0.627	0.525	0.528	0.758	0.721	0.713	0.488	0.605	0.682	0.537
FR	0.522	–	0.488	0.467	0.452	0.575	0.648	0.332	0.489	0.527	0.436
LR	0.644	0.577	–	0.783	0.625	0.593	0.649	0.350	0.653	0.758	0.532
MF	0.649	0.742	0.708	–	0.664	0.550	0.610	0.538	0.524	0.691	0.605
PS	0.555	0.549	0.519	0.606	–	0.738	0.696	0.595	0.627	0.710	0.628
QC	0.617	0.649	0.660	0.744	0.478	–	0.742	0.435	0.834	0.874	0.647
QS	0.647	0.683	0.715	0.655	0.525	0.800	–	0.595	0.549	0.669	0.625
SLP	0.342	0.490	0.383	0.307	0.391	0.434	0.396	–	0.379	0.517	0.645
SN	0.580	0.592	0.718	0.749	0.557	0.714	0.567	0.499	–	0.798	0.543
TPM	0.688	0.735	0.790	0.754	0.559	0.798	0.861	0.441	0.737	–	0.603
UPL	0.522	0.646	0.610	0.446	0.488	0.548	0.635	0.583	0.425	0.620	–

Note(s): The values below the diagonal are HTMT statistics of mass customization, whereas the above the diagonal are HTMT statistics of batch

Table 4.
HTMT statistics (HTMT0.90)

the other hand, in the mass customization, 50% of the variance in MF is explained by LM, and both LM and MF explain 66.70% of the total variance in LR. These figures demonstrate a reasonable and substantial explanatory power of LM on MF and LR in both batch and mass customization processes.

	CL	FR	PS	QC	QS	SLP	SN	TPM	UPL
CL	1	0.631	0.760	0.722	0.715	0.486	0.609	0.683	0.546
FR	0.524	1	0.459	0.576	0.650	0.340	0.493	0.530	0.445
PS	0.556	0.552	1	0.741	0.702	0.595	0.628	0.710	0.644
QC	0.618	0.656	0.483	1	0.745	0.438	0.836	0.873	0.659
QS	0.649	0.689	0.523	0.801	1	0.591	0.554	0.668	0.638
SLP	0.345	0.491	0.395	0.440	0.402	1	0.380	0.514	0.639
SN	0.580	0.595	0.554	0.715	0.567	0.496	1	0.795	0.555
TPM	0.690	0.738	0.560	0.801	0.861	0.445	0.736	1	0.614
UPL	0.523	0.644	0.493	0.552	0.643	0.583	0.430	0.624	1

Note(s): The values below the diagonal are correlations coefficients for batch process, whereas the above diagonal values are correlations coefficients for mass customization. All the correlation coefficients are significant at the 0.05 level (two-tailed)

Table 5. Correlation coefficients among LM practices

		Constructs		
		LM	MF	LR
Batch	Inner VIF	2.950	2.950	–
	R^2	–	0.661	0.657
	f^2	0.470	0.020	–
	Q^2	–	0.381	0.397
Mass customization	Inner VIF	2.000	2.000	–
	R^2	–	0.500	0.667
	f^2	0.163	0.454	–
	Q^2	–	0.316	0.438

Table 6. Structural model assessment results

In conjunction with R^2, f^2 representing the individual effects of the exogenous variable on an endogenous variable by looking at the R^2 changes when an individual predictor is included or excluded into a structural model (Ali *et al.*, 2018). It shows whether the excluded construct has an essential effect on the endogenous construct (Hair *et al.*, 2017). Cohen (1988) provided a guideline on interpreting the f^2; the values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. As shown in Table 6, within the companies implementing batch, LM has a large effect (f^2 = 0.470), while MF provides a small effect (f^2 = 0.020) on LR. However, in the companies implementing mass customization, LM gives a medium effect (f^2 = 0.163), while MF provides a large effect (f^2 = 0.454). Subsequently, Q^2 representing the predictability of the structural model was also assessed through a blindfolding procedure. In a similar vein, it predicts the accuracy of R^2, in which if the Q^2 is higher than 0, the model has a predictive power (Hair *et al.*, 2017). In both structural models (i.e. mass customization and batch), Q^2 values are higher than 0 in both endogenous variables (i.e. MF and LR). Therefore, the structural models have predictive relevance.

The next step of the data analysis is hypotheses testing. A consistent bootstrapping was applied using 5,000 bootstrap samples to derive a 95% bias-corrected bootstrap confidence interval. There is no consensus regarding the number of bootstrap samples that should be generated, except that more is better (Preacher and Hayes, 2008), and should be larger than original samples (Hair *et al.*, 2013). The confidence interval affords additional information regarding the extent to which the true population parameter will fall at a certain level of confidence (Hair *et al.*, 2013). Table 7 presents the results.

For the companies implementing mass customization, Table 7 shows that all the direct and indirect effects in the model are significant at $p < 0.05$. The results indicate the strong

Table 7. Summary of hypotheses testing

Hypothesis: Relationship	Mass customization					Batch				
			Confidence interval					Confidence interval		
	Std. Beta	*t*-value	2.50%	97.50%	Decision	Std. Beta	*t*-value	2.50%	97.50%	Decision
H_2: LM → MF	0.672	7.656*	0.497	0.871	Supported	0.760	18.527*	0.710	0.885	Supported
H_3: LM → LR	0.356	2.289*	0.140	0.666	Supported	0.652	3.448*	0.248	1.041	Supported
H_4: MF → LR	0.491	3.032*	0.106	0.776	Supported	0.144	0.674	−0.252	0.572	Not supported
H_5: LM → MF → LR	0.330	3.061*	0.094	0.607	Supported	0.109	0.662	−0.198	0.482	Not supported

Note(s): $*p < 0.05$ (one-tailed test) positive effects of LM on both MF ($\beta = 0.672$, $t = 7.656$) and LR ($\beta = 0.356$, $t = 2.289$). Similarly, MF also significantly affects LR ($\beta = 0.491$, $t = 3.032$). All the β-values have confidence intervals that do not include zero. Thus, the null hypothesis stating that the β-values equal to zero should be rejected. On the other hand, for the sample companies implementing batch, LM significantly affects both MF ($\beta = 0.760$, $t = 18.527$) and LR ($\beta = 0.652$, $t = 3.448$), with confidence intervals do not contain zero. However, the analysis shows an insignificant impact of MF on LR ($\beta = 0.144$, $t = 0.674$), with a confidence interval of β-value contains zero. Therefore, except for the direct effect of MF on LR for batch showing insignificant effect, all the direct effects are significant at $p < 0.05$. In short, Hypothesis 2 and 3 are supported for both manufacturing processes, while Hypothesis 4 was rejected in the batch process. With regards to the indirect effect, Table 7 shows the significant effect for mass customization ($\beta = 0.330$, $t = 3.061$) and insignificant for the batch process ($\beta = 0.109$, $t = 0.662$). It indicates that there is a positive indirect effect of LM on LR through MF in the mass customization process Hypothesis 5 is supported). However, the indirect effect does not exist within the firms implementing batch. With regards to the mass customization process, MF complementary mediates the effect of LM on FR (Zhao *et al.*, 2010), in which both the indirect and direct effect does exist and point to the same directions (i.e. positive).

Multigroup analysis (PLS-MGA). In this stage, to test whether the path coefficients differ significantly between two groups (Hair *et al.*, 2017; Henseler, 2012), a PLS-MGA was applied. By using this approach, sub-samples based on types of the manufacturing process are compared by using the permutation test. Before the PLS-MGA, to assess the invariance of constructs across multiple groups of data, the three steps of measurement invariance of composite models (MICOM) were followed (Henseler *et al.*, 2016; Matthews, 2017). The three steps are examining configural invariance, compositional invariance, and assessing equality of composite mean values and variances. Configural invariance involves assessment of measurement models for all groups, including a review of the development process of the survey (Matthews, 2017). As the measurement passed content validity, data screening including outlier deletion, as well as construct validity, then configural invariance is established (Henseler *et al.*, 2016; Matthews, 2017). The second step (compositional invariance) was done through a permutation test. Following Matthews (2017), permutations were set 5,000, one-tailed test, 0.05 significance level, and seven stop criterion. The MICOM permutation results also include the third step of its procedure (Henseler, 2012).

In the second step of the MICOM procedure (see Table 8), Matthews (2017) guided that the original correlations should be equal and higher than 5% quantile correlations. Thus, compositional invariance is not a problem in all the constructs. In the third step, the constructs' equality of mean values and variances across groups was evaluated. Table 9 shows the mean original difference falls between the lower (5%) and upper (95%) boundaries as suggested by Matthews (2017) and Henseler (2012). In the second portion of MICOM step 3, Table 9 also shows that the values of variance original differences are the numbers within the 95% confidence interval for all the constructs. As the values are within the 5 and 95% boundaries, it shows the full measurement invariance for the constructs (Henseler, 2012). Thus the measurement models of the two groups can be examined using the pooled data.

After establishing the full measurement invariance, this study tests whether or not the path coefficients differ significantly between two groups (i.e. batch and mass

Table 8.
MICOM step 2 results

	Original correlation	Correlation permutation mean	5%	Permutation p-Values
LM	0.999	1.000	0.999	0.122
LR	1.000	1.000	0.999	0.585
MF	1.000	0.999	0.999	0.669

Table 9. MICOM step 3 results

	Mean-original difference (Batch-MC)	Mean-permutation mean difference (Batch-MC)	5%	95%	Permutation p-Values	Variance-original difference (Batch-MC)	Variance-permutation mean difference (Batch-MC)	5%	95%	Permutation p-Values
LM	0.073	0.001	−0.265	0.270	0.327	0.093	0.013	−0.411	0.445	0.380
LR	0.222	−0.001	−0.262	0.265	0.080	−0.235	0.013	−0.416	0.453	0.171
MF	0.253	0.000	−0.260	0.257	0.053	−0.302	0.012	−0.488	0.490	0.198

Note(s): MC = Mass customization

customization). Table 10 shows the outputs of the permutation procedure. Referring to the table, the direct effect between MF and LR and the indirect effect of LM to LR through MF indicate the significant differences between batch and mass customization, as evident by path coefficient original difference values that fall within the lower and upper boundaries for the 95% confidence intervals (Matthews, 2017). It is also supported by permutation *p*-values of 0.090 and 0.100, respectively, which are less than or equal to the threshold of 0.10 (Henseler, 2012; Matthews, 2017). These indicate that H_6 was partially supported.

Discussion

The outcomes of this study exhibit the significance of the holistic adoption of LM practices in predicting FR and LR in the context of mass customization and batch manufacturing processes. The results show that all the LM practices complement each other and corroborate in a mutually supportive nature, which suggests the simultaneous adoption (supporting Hypothesis 1). It implies the synergistic relationship between the practices, which are valuable for achieving MF and LR. The results provide further confirmation of previous studies (Furlan *et al.*, 2011a, b; Nawanir *et al.*, 2013; Shah and Ward, 2003), which supports the notion of holistic implementation of LM practices, rather than piecemeal, as suggested by complementarity theory (Milgrom and Roberts, 1990, 1995). According to Lee *et al.* (2010), two business units (can be equated with manufacturing practices or activities) may appreciate super-additive value synergies if their combined value is more than the total of their separate values. In short, the value (a, b) is higher than value (a) + value (b). Thus, firms gaining outstanding achievement through the holistic adoption of organizational practices (or activities, assets, etc.) are expected to obtain higher advantages over long periods. The finding of this study, consequently, recommends that companies should invest in all the LM practices simultaneously, rather than picking up one over the other. Additionally, this study conveys a message that the partial adoption of LM practices may fail to enhance the ultimate achievement.

This study also extends the findings of dos Santos Bento and Tontini (2018) by comparing the implementation of LM within two different types of the manufacturing process. The study reveals that samples adopting the mass customization manufacturing process implement LM practices to a greater extent than batch, with a slightly different focus. Mass customization focuses on QS, besides TPM, PS, and FR, whereas the batch emphasizes TPM, QC, SN, and FR. Both put less emphasis on SLP; however, its implementation in mass

	β-Original (batch)	β-Original (MC)	β-Original difference (Batch-MC)	β-Permutation mean difference (Batch-MC)	5%	95%	Permutation *p*-Values
LM → LR	0.652	0.356	0.297	−0.007	−0.371	0.369	0.101
LM → MF	0.760	0.672	0.088	−0.001	−0.168	0.178	0.235
MF → LR	0.144	0.491	−0.348	0.006	−0.438	0.429	0.090
LM → MF → LR	0.109	0.330	−0.221	0.006	−0.285	0.291	0.100

Note(s): β = path coefficient, MC = mass customization

Table 10.
Permutation test path coefficient results

customization higher than in batch. This is consistent with the characteristics of the mass customization system that needs higher flexibility level (Da Silveira *et al.*, 2001; Sandrin *et al.*, 2018), which must be supported by quick setup process, sound maintenance system on machines and equipment, extensive implementation of pull and *kanban* system (Rogers *et al.*, 2011), as well as more flexible resources in terms of machines, equipment, workers, and production lines. All these components are critical in a mass customization process to accommodate the fluctuations and variations of customer demand.

The present study demonstrates the synergistic effect of all the nine LM practices in the form of second-order construct LM on MF and LR. Even though the degrees of LM implementation within the two processes are slightly different, LM positively associates with MF and LR (supporting Hypothesis 2 and 3). The more extensive the implementation of LM, the more flexible the manufacturing system (Fullerton and Wempe, 2009; Khanchanapong *et al.*, 2014), and the lower the lead time (dos Santos Bento and Tontini, 2018; Khanchanapong *et al.*, 2014; Matsui, 2007).

Interestingly, even though LM positively affects MF and LR in both manufacturing processes, with regards to the effect of MF on LR, there is a difference between batch and mass customization. The insignificant effect of MF on LR was found in batch (leading to rejection of Hypothesis 4), which is conversely found in mass customization. This also leads to the absence of the significant indirect effect of LM on LR through MF, which, therefore, implies the rejection of Hypothesis 5. Nevertheless, in the sample companies implementing mass customization, the positive significant indirect effect was found, which supports Hypothesis 5. It suggests unique direct and indirect effects of LM on LR. MF plays a role as a mediating variable in this relationship. It indicates that MF is a critical variable in mass customization (Suzić *et al.*, 2018) to shorten the lead time successfully. To support this fact, the researchers were interested in extending the investigation by applying the importance-performance map analysis (IPMA) using SmartPLS 3.2.8. Figure 1 shows the importance-performance maps (indicators, standardized effect) of both batch and mass customization. The figures (a and b) indicate that MF is vital in mass customization and contributes significantly to LR.

This finding is in line with the opinion from Wang *et al.* (2016), who postulated key capabilities of mass customization, including quick response to a variety of customer demand and the ability to customize products while upholding high volume and consistent quality without incurring high costs. To achieve these capabilities, MF is one of the critical requirements (Suzić *et al.*, 2018). However, flexible workers only would not be sufficient to cater to the requirements and challenges of the mass customization manufacturing process; technology flexibility in terms of machines, equipment, tools, jigs, and fixtures could be a critical element (Brown *et al.*, 2005; Da Silveira *et al.*, 2001). These capabilities may not be available in the batch manufacturing process. Hence, even though LM implementation in a batch manufacturing process leads to higher MF, the MF itself is unable to offer a significant reduction in lead time.

Implications of the study

Theoretical implications

This study considerably subsidizes to the body of knowledge through seeking to the determinants of organizational performance, specifically MF and LR, in the context of mass customization and batch manufacturing processes. From the complementarity theory point of view, this study further shows the mutually collaborative nature of LM practices. The results of the study demonstrated positive interactions among the LM practices in both mass customization and batch manufacturing (Hypothesis 1). It implies that investing in complementarity practices simultaneously would offer superior results rather than either

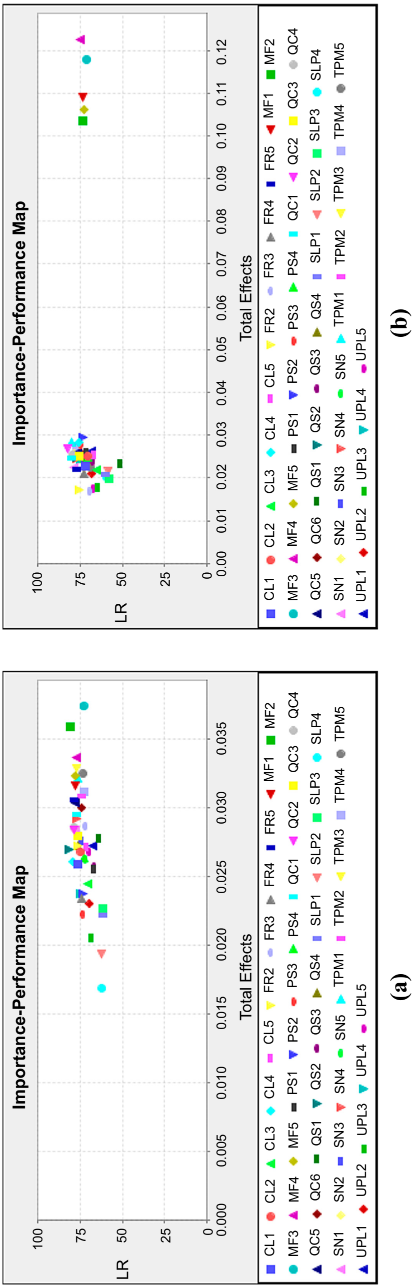

Figure 1.
Importance-performance maps comparison between batch (a) and mass customization (b)

emphasizing on one kind of practice at once or adopting them in isolation (Milgrom and Roberts, 1995). According to the complementarity theory, the return of the collection practices of LM might be higher than deploying each practice individually (Furlan *et al.*, 2011b). As such, consistent with complementarity theory, by which the synergistic effect of LM practices brings better improvement on MF (Hypothesis 2) and LR (Hypothesis 3) in both mass customization and batch processes. This finding coincides with the studies by Sahoo and Yadav (2018), Wickramasinghe and Wickramasinghe (2017), Furlan *et al.* (2011a), Furlan *et al.* (2011b), Nawanir *et al.* (2016), and Shah and Ward (2003), who highlighted the importance of LM bundles towards firms' performance.

This study also provides evidence on the importance of MF in mediating the effect of LM implementation in mass customization manufacturing on LR (Hypothesis 5). It implies that MF is one of the critical factors in mass customization manufacturers to enhance lead time performance as well as perhaps other performance indicators, such as productivity, costs reduction, inventory minimization, sales, customer satisfaction, profits, and business sustainability. This finding is consistent with the characteristics of a mass customization system, in which the companies should be able to cater for fluctuations and variabilities of demand in the current dynamic market (Da Silveira *et al.*, 2001; Sandrin *et al.*, 2018; Suzić *et al.*, 2018; Wang *et al.*, 2016). This finding might be slightly different from the batch manufacturing system. Even though LM can significantly improve the MF, it does not subsequently improve LR (Hypothesis 4 and 5). It entails that MF is less critical in batch, as the system is not targeted to be very flexible as in the mass customization. Therefore, this finding supports the contingency theory (Lawrence and Lorsch, 1967a, b) suggesting that different manufacturing practices and performance measures could fit different companies with different characteristics (Cua *et al.*, 2001; Latan *et al.*, 2018; Shah and Ward, 2003; Tortorella *et al.*, 2018). More importantly, the relationship between the variables may vary based on the context of the study. This context-dependent property suggests to consider specific contexts and situations (e.g. product variety and complexity, production volume, types of process, technology, etc.) at which the manufacturing practices work effectively to leverage organizational performance. Therefore, types of a production process can be a decisive factor in understanding how the LM leads to organizational performance, specifically MF and LR.

Practical implications

The statistical analysis results provide essential insights. First, the strong associations among the LM practices lumped together in a second-order construct recommend the practitioners to implement LM practices simultaneously and holistically to secure the excellent benefits of LM. The practices should not be considered as independent practices; instead, they are dependent on each other (Furlan *et al.*, 2011a, b; Sahoo and Yadav, 2018; Wickramasinghe and Wickramasinghe, 2017). Thus, both types of the manufacturing process should implement LM holistically to leverage their flexibility and lead time performance. Second, the implementation of LM practices and the targeted performance measures should be designed with a specific context in mind in order to avoid their mismatch with organizational characteristics. In other words, they must be tailored depending on the specific organizational context. Third, the mass customization manufacturers should give priority on LM implementation to enhance MF, because LM is the pre-cursor of MF (Ghobakhloo and Azar, 2018), which would lead to other performance measures. Manufacturers should emphasize flexibility enhancement in terms of volume, product mix, routing, machines and technology, and workers (Rogers *et al.*, 2011). Forth, even though this study reveals no effect of MF on LR in batch manufacturing, to sustain, the manufacturers should also undertake their efforts towards flexible manufacturing as in the mass customization system. It is important because customer demand changes over time; besides, flexibility tends to be a pre-requisite for other performance achievements.

Fifth, to enhance the flexibility of manufacturing systems; besides the initiatives of implementing LM practices comprehensively, the manufacturers should consider investing in advanced manufacturing technology (AMT). It is in line with the studies from Khanchanapong *et al.* (2014) and Ghobakhloo and Azar (2018), who suggested supporting LM with AMT. Khanchanapong *et al.* (2014) revealed that LM and AMT were mutually supportive of each other in leveraging manufacturing performance dimensions (e.g. quality, lead-time, flexibility, and cost). On the other hand, Ghobakhloo and Azar (2018) assigned AMT as a determinant of LM and agile manufacturing, which subsequently lead to marketing, operational, and financial performances. Even though both studies assigned AMT in different positions, AMT was considered critical for manufacturers to be concurrently implemented with LM. Even, Suzić *et al.* (2018) highlighted that technology is one of the enablers of mass customization. Ghobakhloo and Azar (2018) also regarded AMT as one of the critical infrastructures for the successful development of LM and flexible manufacturing system, as the value of AMT is truthfully changed to performance improvement when AMT practices, activities and tools are appropriately utilized in manufacturing systems.

Lastly, manufacturing firms must advance their flexibility performance while adopting LM and other collaborative manufacturing strategies (such as flexible manufacturing systems, smart manufacturing systems, etc.) due to the current competitive market with changing customer demand and high uncertainty. This would not only support manufacturers to cope with the ever-changing demand of customers but also would help them to augment their business sustainability performance to the greater height.

Limitations and suggestions for future research

It is necessary to unveil the limitations of the study. Thus they could be deliberated when understanding the results and before taking any possible arrangements based on the outcomes of the study. Firstly, while LM is a long-term initiative (Sahoo and Yadav, 2018), its benefits could not be realized in the short-term. Thus, as an alternative to the cross-sectional study, a longitudinal study could be considered to enhance the accuracy of the inference. Secondly, in this survey, one respondent's company was represented by the response from a single key person (either manufacturing director, manager, or head of a department), which might be influenced by several factors such as work situation, personal point of view, knowledge, etc. Therefore, even though the validity and reliability assessments were satisfactory, which was also supported by the absence of CMV, the respondents' answers may be diverse from the actual conditions of their plants. To obtain more accurate results and resounding inferences, future studies are suggested to consider evidence from several respondents representing a single company, besides combining perceptual and objective measures (such as from annual reports, operational reports, etc.). This may help to confirm the convergence or divergence among different sources of data. Thirdly, this study focused on mass customization and batch manufacturing system; thus, it may restrict the results to this contextual condition. Further investigations in other contexts (such as repetitive, job shop, and even continuous process) could be considered. Lastly, as discussed in the previous section, LM adoption might be supported by its other collaborative strategies (such as AMT, flexible manufacturing, smart manufacturing, etc.) that future studies can take into account. Thus, a more comprehensive point of view could be produced.

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