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Implementing Industry 4.0 and lean practices for business performance in manufacturing: Case of Malaysia

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ABSTRACT

Manufacturing industries had embraced the trend of conceiving a robust manufacturing system and enhancing business performance with the implementation of Industry 4.0 digital technologies and lean manufacturing practices. Despite multiple studies being conducted to identify the correlation between Industry 4.0 digital technologies, lean manufacturing practices, and business performance, ambiguous and conflicting statements are often being debated among researchers. Hence, this study aims to provide empirical evidence gathered from Malaysian manufacturing industries using questionnaires to investigate and model their correlation and explore the mediating influence of Industry 4.0 digital technologies on lean manufacturing practices and business performance using PLS-SEM. Consequently, the findings from 124 respondents were compared with prior studies and revealed that both Lean Manufacturing Practices and Industry 4.0 Digital Technologies are positively correlated with one another, and they positively influence business performance, which findings are coherent with prior studies and fortifying the urgency of implementing both concepts for business performance enhancement. Moreover, this study successfully revealed that Industry 4.0 digital technologies mediate lean manufacturing practices and business performance proving the importance of Industry 4.0 to solving Lean's limitation, which is not studied in prior studies. In addition, the framework in this study is more practical in providing appropriate theoretical and managerial insights for future action and works due to its medium predictive power associated. In a nutshell, this study effectively implies the substantial roles and reinforced the pragmatisms of implementing both lean manufacturing practices and Industry 4.0 digital technologies concurrently for business excellence.

1. Introduction

The fourth industrial revolution (4IR) or Industry 4.0 (I4.0) is deemed as the present paradigm shift in manufacturing since 'Hannover Messe' in 2011. Subsequently, the anthology of cutting-edge technologies associated with I4.0 was heavily utilized in numerous novel frameworks and concepts with an assurance of vast evolution in manufacturing technologies and processes, offering new business models and capabilities to organizations that were not viable before (Pereira et al., 2019).

Alternatively, Lean Manufacturing Practices (LMP) is recognized as the salient success factor for many organizations in the past few decades with its straightforward yet capable combination of implementation techniques and tools (Sanders et al., 2016). LMP is to guarantee that cost reduction is achieved via waste elimination, enhancing flow, gratifying customer demands, empowering employees, and generating brand-new values for products and services offered (Ohno, 2019; Liker, 2004).

Accordingly, decision-makers and top management are compelled to apply both approaches to their respective manufacturing firms to enhance performance and be agile (Sanders et al., 2017). Unfortunately, this process has created various complications, especially regarding

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compatibility and sustainability. According to Kamble et al. (2020), this issue is much more aggravated as the risk of losing out by not implementing them concurrently is excruciating. Consequently, many scholars and researchers attempt to solve the predicament faced with numerous studies completed to rationalize their compatibility. However, inconsistent findings are frequently issued among researchers, resulting in even greater bewilderment (Ejsmont and Gładysz, 2020) as prior literature concentrates on systematic literature review, and conceptual framework instead of empirically validated research to substantiate those claims (Kolberg and Zühlke, 2015).

Hence, the main aim of this paper is to delve into the association between LMP and Industry 4.0 Digital Technologies (I4.0 DT) as well as their execution level in Malaysia. Likewise, prior literature only attempted to solve the correlation between LMP and I4.0 DT. However, this paper intends to delve beyond by mapping their association with Business Performance (BP) based on empirical data collected from industries using Partial Least Squares Structural Equation Modelling (PLS-SEM). Additionally, most empirical studies tend to focus on assessing their direct correlation with BP; however, this paper intends to also learn about the mediating influence of I4.0 DT affecting LMP on BP. As a result, this novelty can provide justification and newfound knowledge regarding the inconsistent understanding of their compatibility and eventually narrow the literature gap. Those insights are vital to providing aid to decision-makers and top management to strategies their transition plan in implementing both I4.0 DT and LMP.

This paper is organized as follows: Section 1 presents the introduction of this paper. Section 2 exhibits the background of the studied topic and the proposed research model. Section 3 explains the research methodology for conducting this study. Section 4 provides the main findings based on the data analysis. Section 5 discusses the findings, and lastly, Section 6 will conclude the results.

2. Theoretical background

2.1. Industry 4.0

Manufacturing firms globally have appreciated new technological advancements as well as the outcome of globalization resulting in a borderless marketplace facilitating them to earn huge profits and benefits (Prinz et al., 2018). However, this has also increased the challenges and difficulties faced by organizations, such as rapid product developments, rapid customer shifts in demands, mass customizations, sustainability, environmental issues, etc. Therefore, this has successfully stimulated the desire for differentiation among the competition, and the ultimate solution is to implement I4.0 DT in their respective organizations (Prinz et al., 2018). As a result, I4.0 DT has grabbed the spotlight globally in the last decade (Pereira et al., 2019).

This enormous advancement of those technologies drastically altered the landscape of manufacturing practices and processes. According to Schmidt et al. (2015), it is said that the advancement of I4.0 is more significant as compared with the three previous industrial revolutions. As a recap, the first industrial revolution began at the end of the 18th century in Britain, with the invention of steam and waterpower. The second industrial revolution was initiated at the end of the 19th century, with the invention of electricity replacing steam and internal combustion engine promoting efficient transportation. Also, mass production developed during this era enabling cost savings. In the middle of the 20th century, the transition from analog to digital electronics occurred with the development of semiconductors and integrated circuit boards like the computer, and Information Technology (IT) prompted the third industrial revolution (Klingenberg et al., 2022; Rojko, 2017).

I4.0 can be classified with 'technology trends' and 'design principles' (Ghobakhloo, 2018). Technology trends are based upon the existence of prominent solutions with the utilization of cutting-edge digital technologies like Big Data Analytics (BDA), Cyber-Physical System (CPS), Internet of Things (IoT), sensors, Artificial Intelligence (AI), Additive Manufacturing, Virtual Reality (VR), Augmented Reality (AR), RFID, etc. (Kusiak, 2019; Vogel-Heuser and Hess, 2016). Next, design principles allow practitioners to strategies and estimate the development of I4.0 adoption derived from the design principle of I4.0, which aims to attain improvements and advantages of I4.0 (Ghobakhloo, 2018; Santos et al., 2017). These 'design principles' are 'service orientation,' 'real-time capability,' 'interoperability,' 'modularity,' 'decentralization,' and 'virtualization' (Ghobakhloo, 2018; Tortorella and Fettermann, 2018).

According to researchers, I4.0 DT promised to bring quantum leaps of improvements that were not viable in the past. Some examples are cost reductions, less reliance on labor forces and low-skilled workers, new business models offered in products and services, quick product and service launching, wastage and defects reduction, flexibility, agility, quickly adapting to changes, mass product customization, better allocation of resources and workforce, reduce lead time, etc. (Sony, 2018; Lee et al., 2017; Bédard-Maltais, 2017; Mohamed, 2018). Despite so, researchers argued that those advantages discussed are only stated hypothetically as opposed to presenting effective case studies and empirical data to support the numerous advantages offered by implementing I4.0 DT in organizations (Buer et al., 2018; Ejsmont and Gładysz, 2020; Kolberg and Zühlke, 2015; Sony, 2018; Tortorella and Fettermann, 2018). As a result, this present study will want to examine the implication of implementing I4.0 DT toward BP using empirical data from manufacturing firms in Malaysia.

2.2. Lean manufacturing practices

Lean Manufacturing Practices (LMP) is a systematic methodology concentrating on achieving operational excellence with the removal of Lean wastes, also known as 'Muda' (Womack and Jones, 1997) or non-value-adding activities that do not generate value for customers with the creation of a culture of continuous improvement, customer orientated, flow, empowering employees, standardization of processes, etc. with the utilization of a wide range of tools and techniques (Bhamu and Sangwan, 2014; Liker, 2004; Ohno, 2019; Shah and Ward, 2003; Womack and Jones, 1997). With the outstanding capabilities of LMP, LMP is recognized as the best practice for manufacturing firms since the 1980s and is still regarded similarly today (Bhamu and Sangwan, 2014; Garza-Reyes, 2015; Liker, 2004). Some examples of LMP tools and techniques are (Shah and Ward, 2007): Total Preventive Maintenance (TPM), Customer Involvement, Just-in-Time (JIT), Setup Reduction, Supplier Management Implementation, Employee Involvement, Total Quality Management (TQM), Pull Production, Continuous Flow, etc.

Nevertheless, LMP is believed to have reached its maximum potential in this technological advance and globalized era (Kolberg and Zühlke, 2015), as the ability of LMP in the non-repetitive setting is always dubious and deemed the main drawback due to its lack of changeability in the production line. This issue has become even more severe due to the evolution of present customer demands into highly customized products and services as well as shorter product lifecycles (Buer et al., 2018). It is claimed that this issue has even plagued organizations that significantly utilize LMP where modifications cannot be done rapidly to meet the current turbulent market. This is because the deviation of demands in the market is always contradictory to LMP's leveled capacity utilization which leans heavily upon the forecast of market demands (Buer et al., 2018; Kolberg and Zühlke, 2015; Sony, 2018; Tortorella and Fettermann, 2018). In addition, Kolberg and Zühlke (2015) argued that LMP does not consider digital technologies as most of its philosophies and principles were developed before the computing age.

To be concise, researchers and academicians claimed that LMP is unable to cope with the future market and only utilizing I4.0 DT in manufacturing firms is the evolutionary way to go (Buer et al., 2018; Kolberg and Zühlke, 2015; Rüttimann and Stöckli, 2016; Tortorella and Fettermann, 2018). Hence, this study is prompt to empirically study the mediating effects of I4.0 DT on LMP and BP.

2.3. Industry 4.0 and lean manufacturing practices

The main focus of this article is to explore the correlation of LMP and I4.0 DT as well as to evaluate their implication for BP; thus, it is vital to thoroughly comprehend their correlation based on present literature to develop a proposed framework that is proficient in representing the correlation between them.

Based on Kolberg et al. (2017), the history of their relationship started with the creation of the Toyota Production System (TPS), the precursor of LM, where Ohno (2019) Taiichi-creator of TPS had specified that with the term 'autonomation,' repetitive and value-added activities must be automated as well as machinery must have the intelligence of detecting and stopping abnormalities (Ohno, 2019). This concept is analogous to the implementation of CPS of I4.0. Next, their path crossed again in the 1990s with the concept of 'Lean Automation' (Kolberg and Zühlke, 2015; Kolberg et al., 2017). However, the concept failed as substantial application limitations were due to the limited computer capabilities and exorbitant investing costs. Nevertheless, this concept is reignited with state-of-the-art digital technologies of I4.0 that can solve those limitations (Tortorella et al., 2021).

As claimed by both Kolberg and Zühlke (2015), and Pereira et al. (2019), academicians and researchers' spark of interest in I4.0 DT and LMP has increased over the years as decision-makers and practitioners are keen to integrate and apply both simultaneously. However, based on studies conducted by many researchers (Buer et al., 2018; Kolberg and Zühlke, 2015; Pereira et al., 2019; Rüttimann and Stöckli, 2016; Tortorella and Fettermann, 2018; Sony, 2018), the correlation between LMP and I4.0 is still ambiguous as well as lacks empirical data to support their positive correlation for implementing and integrating them both as prior studies are the conceptual framework for integration (Ante et al., 2018; Prinz et al., 2018; Sanders et al., 2017; Satoglu et al., 2018; Sony, 2018); or literature review on the related topic with the implication (Bittencourt et al., 2019, 2021; Buer et al., 2018; Davies et al., 2017; Pereira et al., 2019). Although there are case studies done (Ma et al., 2017; Mrugalska and Wyrwicka, 2017; Powell et al., 2018; Wagner et al., 2017), they have only managed to prove their accomplishment based on proprietary solutions with specific purposes. Thus, modularisation and interchangeabilities with other systems are limited and unknown (Buer et al., 2018). Moreover, this does not fulfill the characteristics and advantages of I4.0 that allow modularisation, interchangeability, and system integration (Ghobakhloo, 2018; Kolberg et al., 2017). To be brief, this undoubtedly implied a preliminary empirical study on the successful integration of LMP and I4.0 and their positive correlations that can benefit organizations (Pereira et al., 2019). Hence, this study would want to offer novel findings with empirical data relating to the correlation of LMP and I4.0 with BP while also I4.0 as the mediator for LMP and BP.

Subsequently, as there is a lack of empirical data to establish those claims as discussed earlier, inconsistent remarks are frequently being discussed by researchers and academicians arguing about their feasibilities and capabilities to sustain and obtain desirable improvement. This regrettably instigated greater misperception among decision-makers and top management, leading them to disregard these novel concepts further. However, researchers predominantly concurred with the optimistic correlation between LM and I4.0 implementation as both goals are to accomplish simplification, decentralizing vast and complicated machinery, and both focus on increasing productivity (Buer et al., 2018; Kolberg and Zühlke, 2015). Some of the researchers had even claimed that without LMP as the foundation or prerequisite for I4.0 DT implementation, I4.0 DT implemented in that organization will face a high risk of failure (Buer et al., 2018; Rüttimann and Stöckli, 2016; Tortorella and Fettermann, 2018). Furthermore, the shortage of empirical data to establish the favorable implication of I4.0 DT on BP and its sustainability must be thought too. Hence, the easiest way of implementing I4.0 DT should be complemented with the vigorously recognized LMP (Tortorella et al., 2019). This statement is further supported by Bortolotti et al. (2009) and Nicoletti (2013), arguing that digitalizing an ineffective chokepoint process will not improve the condition. In addition, researchers have argued that with the foundation of LMP, the risk associated with the implementation would be significantly reduced, and the rate of implementation can be significantly improved due to existing LMP's characteristics of transparency, simplification, continuous flow, and standardization (Buer et al., 2018; Rüttimann and Stöckli, 2016; Sanders et al., 2017). As a result, the integration of LM and I4.0 will propel companies to a whole new level with better LMP maturity, more accurate data, solving LMP limitations, distributed computing and autonomy, real-time information sharing, improved productivity, etc. (Buer et al., 2018; Kolberg and Zühlke, 2015; Tortorella and Fettermann, 2018).

On the contrary, several studies indicated conflicting beliefs on the correlation between LMP and I4.0 DT. For example, Sanders et al. (2016, 2017) argued that LMP focuses on diminishing system complexity, whereas the intricacy of I4.0 DT itself will increase the complexity of those systems. This statement contradicted the pioneer case study on the integration of both LMP and I4.0 DT (Kolberg and Zühlke, 2015), where they claimed that both concepts have similar aspirations to decentralize and reduce complexity. Also, Rüttimann and Stöckli (2016) claimed that LMP could reduce variation, but I4.0 DT itself will increase variations. Next, both Sommer (2015) and Rüttimann and Stöckli (2016) claimed that only large multinational corporations could achieve the benefit of I4.0 DT, with Small and Medium Enterprises (SMEs) eventually becoming the casualty with a great risk of being substituted. This is due to I4.0 DT's capability of mass-producing highly customized products that were not feasible previously in mass-production plants of large multinational corporations. Also, the huge investment cost and lack of highly skilled workers will hinder SMEs from executing I4.0 DT. Lastly, Strandhagen et al. (2017) claimed that monotonous firms are more likely to transition and benefit from I4.0 DT than non-monotonous firms.

In short, the discussion above demonstrates the urgency for empirical data to bridge the gap in the literature regarding the feasibility and compatibility of the application of both LMP with I4.0 DT and the implication of I4.0 DT towards BP.

2.4. Hypotheses creation and proposed model

Concerning the above discussion, hypotheses were developed to demonstrate the causal links based on the proposed framework, as presented in Fig. 1. This consists of the analysis of the direct linkage of LMP, I4.0 DT on BP, and the direct linkage of LMP on I4.0 DT. In addition, the study continues to examine the mediation influence of I4.0 DT on LMP and BP. Therefore, in this study, four hypotheses were established and shown below:

H1: Lean Manufacturing Practices positively influence Business Performance.
H2: Lean Manufacturing Practices positively influence Industry 4.0 Digital Technologies.
H3: Industry 4.0 Digital Technologies positively influence Business Performance.
H4: Industry 4.0 Digital Technologies mediates the correlation between Lean Manufacturing Practices and Business Performance.

3. Methodology

This present study was devised with a quantitative strategy with a cross-sectional electronic questionnaire-based survey through Google Forms to accumulate empirical data from manufacturing firms for examining the hypotheses and the suggested framework. The population is the manufacturing firms in Malaysia. The criterion of the sample population is the inclusion of all industrial sectors regardless of their size and sales turnover. It is similarly defined based on the criterion described by Tortorella and Fettermann (2018) to safeguard all potential firms participating due to the novelty of these concepts. Furthermore, since the questionnaire design requires the respondent to have specific knowledge regarding I4.0 and LMP, a criterion of a minimum of two years of experience in the related discipline is mandated to improve the consistency and authenticity of accumulated data. Hence, the sampled population will involve employees of manufacturing firms in Malaysia, and a purposive sampling approach was applied in this study to recruit a single respondent representing their manufacturing firm in Malaysia.

Four main sections were devised for the questionnaire with measurement items of the constructs adapted and adopted from previous literature that was statistically proven. Section 1 aimed to gather the respondents' and companies' demographic profiles. Section 2 was conceived with 41 measurement items adopted from Shah and Ward

(2007) with the intent to assess the degree of LMP utilization. Section 3 was developed with 17 measurement items adapted from numerous sources (Ghobakhloo and Ching, 2019; Kamble et al., 2020; MITI, 2018; Rossini et al., 2019; Tortorella and Fettermann, 2018) to quantify the intensity of execution of I4.0 DT. Lastly, section 4 was developed to assess the BP of the respondent's manufacturing firm with 15 measurement items adapted from Ghobakhloo and Fathi (2019), Imran et al. (2018), Nawanir (2016), Ng and Ghobakhloo (2018), Rossini et al. (2019), and Szász et al. (2020).

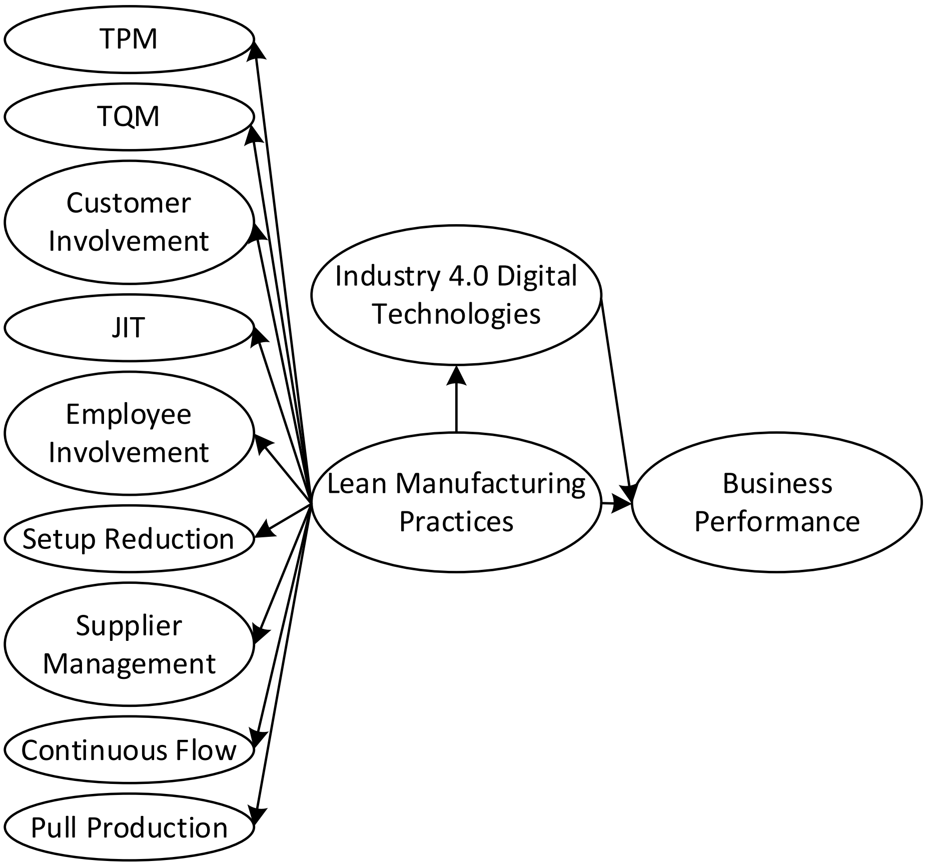

Fig. 1: Proposed research framework

The questionnaire utilized a 5-point Likert scale (1–'Strongly Disagree' toward 5–'Strongly Agree') to estimate the degree of application of LMP and I4.0 DT, as well as the performance of the respondent's manufacturing firm. The pre-testing process was achieved with ten targeted respondents to ensure the questionnaire's relevance, appropriateness, and clarity concerning the study's objectives and provide suggestions for fine-tuning.

As a result, 127 responses were collected in 6 months, with follow-up phone calls and emails being used to increase the rate of responses. Since the questionnaire was designed where all questions must be answered, the concern of missing values is eliminated thoroughly. However, three responses were excluded as a result of the repetitive response from a repeating manufacturing firm, where a final of 124 valid responses was used for subsequent data analysis. The responses corresponded with the minimum sample size required-65 for respondents that were proposed by Hair et al. (2016, 2009), Kline (2015), and Sarstedt et al. (2022) with the usage of G*Power (power analysis software). The configuration for G*Power is predetermined with the following parameters to obtain the minimum sample size (Faul et al., 2007, 2009; Hair et al., 2016):

1. Minimum power (1-β): 0.80
2. Effect size (f2): 0.15
3. Level of significance (α): 0.05
4. Numbers of predictors: 2

4. Results and data analysis

Data collected from manufacturing firms was scrutinized and mapped with the PLS-SEM technique by utilizing SmartPLS 3.38 (Ringle et al., 2015). However, before PLS-SEM, Mardia's (1970) coefficient procedure is conducted to assess the multivariate normality of the empirical data compiled (Mardia, 1970). The findings indicated that the kurtosis coefficient, β of the data, is 22.284, slightly beyond the tolerance limit of 20. Therefore, the data is not normally distributed (Byrne, 2013; Kline, 2015). This reaffirmed the pertinence of utilizing the PLS-SEM technique for data analysis as opposed to Covariance-based Structural Equation Modelling (CB-SEM). To understand more, please read (Hair et al., 2017a). Next, since it is accumulated from a single source, common method variance (CMV) bias must be evaluated to substantiate that the strength of those constructs' relationship is not exaggerated. Harman's single factor (Podsakoff et al.,

2003) and the full collinearity method (Kock and Lynn, 2012) were commonly used to assess CMV bias. Hence, it is safely concluded that CMV bias is not a concern in this present study as the findings from Harman's single factor indicates largest variance described by an individual factor is only 44.004%, which is less than 50%, and for full collinearity method, the VIF value of the random dummy variable based on Table 1 is way less than the threshold value of 3.3.

Table 1: Full collinearity assessment

Variable	VIF
BP	1.868
I4.0 DT	1.427
LMP	1.746

Note: Variance inflation factor (VIF); VIF<3.3

4.1. Assessment of measurement model

The measurement model is assessed to evaluate the validity and reliability of the constructs and their measurement items (Hair et al., 2016). To evaluate the measurement model, three salient stages are accomplished (Hair et al., 2016; Ramayah et al., 2018; Wong, 2019):

1. Internal consistency reliability
2. Outer loadings and convergent reliability
3. Discriminant validity

To guarantee internal consistency reliability, Cronbach's Alpha (α) (Nunnally and Bernstein, 1995) and Composite Reliability (CR) (Hair et al., 2016) must be above the value of 0.7 and 0.708 accordingly. All measurement items in Table 2 are beyond both α's and CR's threshold values proposed. Next, to certify that each measurement items are reliable, the outer loadings must be above 0.708 (Hair et al., 2016). However, based on the findings presented in Table 2, the range of outer loadings varies from 0.582 to 0.925. Byrne (2016) and Hair et al. (2016) stated that outer loadings above 0.5 should be accepted, and deletion is only essential if the Average Variance Extracted (AVE) value and CR value is less than their respective threshold value of 0.5 and 0.708 (Bagozzi and Yi, 1988; Fornell and Larcker, 1981). So, since the findings in Table 2 indicates that the AVE and CR value is above the threshold value, no items were removed. Also, all measurement items fulfilled convergent reliability. Lastly, discriminant validity assessment is done by applying the heterotrait-monotrait (HTMT) criterion. Based on Table 3, all constructs exhibited discriminant validity as they had satisfied the strictest HTMT criterion of a value less than 0.85 (Kline, 2015).

Table 2: Measurement model

Variable	Item	OL	α	CR	AVE
Business performance (BP)	BP1	0.816	0.978	0.980	0.766
	BP2	0.863			
	BP3	0.824			
	BP4	0.809			
	BP5	0.885			
	BP6	0.876			
	BP7	0.886			
	BP8	0.880			
	BP9	0.898			
	BP10	0.902			
	BP11	0.894			
	BP12	0.893			
	BP13	0.925			
	BP14	0.881			
	BP15	0.884			
Just-in-time (JIT)	JIT1	0.802	0.798	0.868	0.623
	JIT2	0.811			
	JIT3	0.823			
	JIT4	0.717			
Pull production (PP)	PP1	0.854	0.905	0.932	0.774
	PP2	0.888			
	PP3	0.898			
	PP4	0.880			
Employee involvement (EI)	EI1	0.838	0.850	0.899	0.690
	EI2	0.872			
	EI3	0.805			
	EI4	0.806			
Supplier management implementation (SMI)	SMI1	0.885	0.890	0.917	0.653
	SMI2	0.892			
	SMI3	0.856			
	SMI4	0.582			
	SMI5	0.855			
	SMI6	0.731			
Setup reduction (SR)	SR1	0.920	0.893	0.933	0.823
	SR2	0.919			
	SR3	0.882			

Variable	Item	OL	α	CR	AVE
Continuous flow (CF)	CF1	0.898	0.911	0.937	0.789
	CF2	0.893			
	CF3	0.911			
	CF4	0.850			
Customer involvement (CI)	CI1	0.897	0.933	0.949	0.790
	CI2	0.908			
	CI3	0.884			
	CI4	0.902			
	CI5	0.851			
Industry 4.0 digital technologies (I4.0 DT)	DT1	0.715	0.969	0.971	0.666
	DT2	0.768			
	DT3	0.826			
	DT4	0.833			
	DT5	0.829			
	DT6	0.884			
	DT7	0.841			
	DT8	0.807			
	DT9	0.850			
	DT10	0.903			
	DT11	0.817			
	DT12	0.822			
	DT13	0.880			
	DT14	0.761			
	DT15	0.819			
	DT16	0.720			
	DT17	0.771			
Total preventive maintenance (TPM)	TPM1	0.883	0.893	0.926	0.757
	TPM2	0.848			
	TPM3	0.904			
	TPM4	0.846			
Total quality management (TQM)	TQM1	0.799	0.919	0.935	0.672
	TQM2	0.850			
	TQM3	0.824			
	TQM4	0.856			
	TQM5	0.754			
	TQM6	0.826			
	TQM7	0.827			

Notes: Outer loadings (OL); Cronbach's alpha (α); Composite reliability (CR); Average variance extracted (AVE)

Table 3: Discriminant validity–HTMT criterion

	1	2	3	4	5	6	7	8	9	10	11
1. BP											
2. CF	0.473										
3. CI	0.598	0.556									
4. EI	0.496	0.555	0.575								
5. I4.0 DT	0.604	0.471	0.385	0.568							
6. JIT	0.637	0.629	0.710	0.600	0.585						
7. PP	0.474	0.781	0.775	0.631	0.404	0.666					
8. SR	0.553	0.770	0.662	0.620	0.495	0.670	0.832				
9. SMI	0.706	0.734	0.765	0.652	0.542	0.785	0.734	0.818			
10. TPM	0.632	0.532	0.583	0.495	0.551	0.802	0.433	0.582	0.607		
11. TQM	0.588	0.655	0.597	0.609	0.675	0.826	0.621	0.760	0.699	0.765	

Notes: HTMT<0.85; BP: Business performance; CI: Customer involvement; CF: Continuous flow; EI: Employee involvement; PP: Pull production; SR: Setup reduction; SMI: Supplier management implementation

4.2. Assessment of higher-order construct

LMP is presented as a higher-order construct (HOC) and measured reflectively with nine lower-order constructs: Continuous flow, TQM, JIT, TPM, customer involvement, employee involvement, pull production, supplier management implementation, and setup reduction. The disjoint-two-stage approach was used to evaluate the HOC (Becker et al., 2012; Cheah et al., 2019; Sarstedt et al., 2019). For the first stage, the assessment of lower-order construct was assessed using the typical measurement model assessment as demonstrated earlier. For the second stage, the latent variable scores for the lower-order constructs were used as the measurement items for the HOC, whereas the remaining variables that are not sub-constructs of HOC are assessed similarly based on the criterion of the measurement model (Hair et al., 2017b; Sarstedt et al., 2019). Table 4 indicates that the internal consistency reliability (Cronbach's α and CR), outer loadings, and AVE value had fulfilled their respective criterion. Similarly, for discriminant validity tabulated in Table 5, all the constructs fulfilled the sternest criterion of HTMT value. In a nutshell, the HOC measurement model has fulfilled all the assessment criteria and will advance to the structural model assessment.

Table 4: Assessment of higher-order constructs

Variable	Item	OL	α	CR	AVE	Variable	Item	OL	α	CR	AVE
Business performance (BP)	BP1	0.821	0.978	0.980	0.766	Industry 4.0 digital technologies (I4.0 DT)	DT1	0.719	0.969	0.971	0.665
	BP2	0.869					DT2	0.773			
	BP3	0.829					DT3	0.826			
	BP4	0.814					DT4	0.835			
	BP5	0.886					DT5	0.830			
	BP6	0.875					DT6	0.882			
	BP7	0.883					DT7	0.838			
	BP8	0.878					DT8	0.806			
	BP9	0.895					DT9	0.846			
	BP10	0.903					DT10	0.900			
	BP11	0.891					DT11	0.818			
	BP12	0.890					DT12	0.821			
	BP13	0.922					DT13	0.881			
	BP14	0.879					DT14	0.761			
	BP15	0.881					DT15	0.817			
Lean manufacturing practices (LMP)	CF	0.786	0.931	0.942	0.644		DT16	0.716			
	CI	0.792					DT17	0.770			
	EI	0.711									
	JIT	0.815									
	PP	0.811									
	SMI	0.863									
	SR	0.841									
	TPM	0.749									
	TQM	0.845									

Note: Outer loadings (OL); Cronbach's alpha (α); Composite reliability (CR); Average variance extracted (AVE)

Table 5: Discriminant validity–htmt criterion for higher-order construct

	1	2	3
1. Business performance			
2. Industry 4.0 digital technologies	0.604		
3. Lean manufacturing practices	0.705	0.638	

Note: HTMT<0.85

4.3. Assessment of structural model and mediation: Hypotheses testing

Structural model assessment is evaluated with five systematic steps proposed by Hair et al. (2016):

1. Assessment of collinearity (VIF) (Becker et al., 2015)
2. Path coefficient (Hair et al., 2016)
3. Coefficient of determination, R^2 (Hair et al., 2016)
4. Cohen's (1988) effect size, f^2 (Cohen, 1988)
5. Predictive relevance using Q^2 (Geisser, 1974; Stone, 1974) and PLSPredict (Shmueli et al., 2016, 2019).

The structural model assessment aims to gauge whether the proposed model was empirically validated and supported by the data collected (Hair et al., 2016).

Assessment of collinearity ensures that all constructs are distinguishable (Hair et al., 2016). Based on Table 6 presented, collinearity is not a concern in this study where VIF values are below the threshold value of 3 as proposed by Becker et al. (2015).

Subsequently, the hypotheses were formulated, and the proposed framework's path coefficient was evaluated using bootstrapping (a non-parametric test) with an iteration of 5000 subsamples. The findings are presented in Table 6. Both H1 (I4.0 DT) and H2 (LMP) have a direct and positive effect on BP with a positive standardized β value of 0.288 and 0.500, t-value of 2.698 and 4.602, p-value of 0.004 and 0.000, and confidence interval of 0.107-0.455 and 0.329-0.682 respectively. Furthermore, for H3, LMP is also found to have a direct and positive effect on I4.0 DT with a positive standardized β value of 0.630, t-value of 9.117, p-value of 0.000, and confidence interval of 0.492-0.726. Therefore, all hypotheses from H1 to H3 are established and accepted based on all the criteria assessed. Moreover, to test for the mediation and indirect effects of H4, (Preacher and Hayes, 2004, 2008) bootstrapping method was applied. H4 is statistically significant with a positive indirect β value of 0.181, a t-value of 2.779, a p-value of 0.005, and a confidence interval of 0.055-0.311. Therefore, it can be concluded that I4.0 DT mediates the correlation between LMP and BP.

Table 6: Structural model assessment and hypotheses testing

Path Relationship	Std. Beta	Indirect effect	Std. Error	t-value	p-value	Confidence interval	R^2	f^2	Q^2	Decision
H1) I4.0 DT->BP	0.288		0.107	2.698	0.004**	(0.107, 0.455)	0.514	0.103	0.381	Supported
H2) LMP->BP	0.500		0.109	4.602	0.000**	(0.329, 0.682)		0.310		Supported
H3) LMP->I4.0 DT	0.630		0.069	9.117	0.000**	(0.492, 0.726)	0.397	0.658	0.240	Supported
H4) LMP->I4.0 DT->BP		0.181	0.065	2.779	0.005**	(0.055, 0.311)				Supported

Note: t-value>1.645; p-value<0.05*, <0.01**; Q^2>0; LMP (Lean manufacturing practices); I4.0 DT (I4.0 digital technologies); BP (Business performance)

The following step is to evaluate the coefficient of determination, R^2. Based on Hair et al. (2016), R^2 values larger than 0.75, 0.50, and 0.25 can be inferred as substantial, moderate, and weak, respectively. Table 6 illustrates that 51.4% of the variance in BP can be described with LMP and I4.0 DT, whereas LMP can justify 39.7% of the variance in I4.0 DT. Hence, it is agreed that BP has moderate predictive accuracy while I4.0 DT has weak predictive accuracy.

Subsequently, the following assessment assesses Cohen's (1988) effect size, f^2. According to Cohen (1988), the effect size, f^2 with values of 0.02, 0.15, and 0.35 represents small, medium, and large correspondingly. Henceforth, Table 6 indicated that I4.0 DT and LMP with values of 0.103 and 0.658 had demonstrated small and medium effect sizes, respectively, in establishing R^2 for BP. On the contrary, LMP demonstrated a large effect size with a value of 0.658 in forming R^2 for I4.0 DT.

Finally, predictive relevance was evaluated with the blindfolding method to obtain the Q^2 value (Geisser, 1974; Stone, 1974). Based on Table 6, it can be inferred that both BP and I4.0 DT had demonstrated predictive relevance with values of 0.381 and 0.240, respectively, where Geisser (1974) and Stone (1974) indicated that the Q^2 value larger than zero implies predictive relevance. To further evaluate the predictive relevance, (Shmueli et al., 2016, 2019; Hair et al., 2019; Sharma et al., 2021) proposed a robust technique known as PLSPredict. Based on the results tabulated in Table 7, the majority of the Q^2 value of the PLS-SEM model estimation is higher than the linear regression model (LM), further establishing the predictive relevance. Next, based on guidelines by Shmueli et al. (2019), the results in Table 7 can be concise in that both constructs have medium predictive power as the majority Root Mean Squared Error (RSME) value and Mean Absolute Error (MAE) value of the PLS-SEM estimation is smaller than the LM model.

4.4. Result benchmark

The results of this empirical study are gauged and compared with prior studies in pursuance of bringing substantial meaningful insight to broaden the literature and knowledge of both LMP and I4.0 DT as well as to solve the ambiguity and contradicting views regarding the compatibility of LMP and I4.0 DT. This study favors an unorthodox approach by offering novel insights into identifying the correlation of LMP, I4.0 DT, and BP of manufacturing industries situated in Malaysia with the usage of PLS-SEM, a causal-predictive approach, as opposed to prior studies illustrating the correlation of LMP and I4.0 DT with operational performance in Norway using hierarchical multiple regression analysis (Buer et al., 2021) and the correlation of LMP and I4.0 DT with sustainability performance in India using CB-SEM (Kamble et al., 2020).

Kamble et al. (2020) successfully disclosed the positive and direct consequence of I4.0 DT on both LMP and sustainable performance. LMP plays a positive role in mediating I4.0 DT and sustainable performance. In contrast, this study suggested a distinct approach to examine the positive mediating effect of I4.0 DT on LMP and BP which has received little to no attention despite researchers had claimed that LMP had reached its limit in this challenging era (Kolberg and Zühlke, 2015).

Table 7: Assessment of PLSpredict

	PLS-SEM			LM			PLS-SEM-LM		
	RMSE	MAE	Q^2_predict	RMSE	MAE	Q^2_predict	RMSE	MAE	Q^2_predict
BP1	0.672	0.492	0.309	0.701	0.514	0.247	-0.029	-0.022	0.062
BP2	0.673	0.489	0.373	0.710	0.501	0.303	-0.037	-0.012	0.070
BP3	0.749	0.601	0.364	0.770	0.621	0.327	-0.021	-0.020	0.037
BP4	0.756	0.599	0.371	0.764	0.606	0.358	-0.008	-0.007	0.013
BP5	0.676	0.521	0.430	0.680	0.525	0.422	-0.004	-0.004	0.008
BP6	0.702	0.557	0.391	0.692	0.554	0.408	0.010	0.003	-0.017
BP7	0.735	0.568	0.298	0.743	0.562	0.282	-0.008	0.006	0.016
BP8	0.663	0.474	0.326	0.684	0.493	0.283	-0.021	-0.019	0.043
BP9	0.764	0.576	0.223	0.791	0.578	0.167	-0.027	-0.002	0.056
BP10	0.661	0.466	0.369	0.693	0.483	0.307	-0.032	-0.017	0.062
BP11	0.585	0.413	0.404	0.572	0.415	0.430	0.013	-0.002	-0.026
BP12	0.713	0.540	0.282	0.719	0.568	0.269	-0.006	-0.028	0.013
BP13	0.731	0.552	0.291	0.723	0.562	0.308	0.008	-0.010	-0.017
BP14	0.712	0.533	0.279	0.704	0.550	0.296	0.008	-0.017	-0.017
BP15	0.797	0.610	0.274	0.766	0.600	0.328	0.031	0.010	-0.054
DT1	0.852	0.696	0.284	0.856	0.668	0.277	-0.004	0.027	0.007
DT2	0.751	0.610	0.377	0.748	0.595	0.382	0.003	0.015	-0.005
DT3	0.851	0.700	0.347	0.867	0.667	0.322	-0.016	0.033	0.025
DT4	0.854	0.669	0.291	0.892	0.675	0.227	-0.038	-0.006	0.064
DT5	0.869	0.679	0.336	0.886	0.684	0.311	-0.016	-0.005	0.025
DT6	1.009	0.794	0.266	1.021	0.810	0.247	-0.013	-0.016	0.018
DT7	1.002	0.797	0.228	1.029	0.831	0.185	-0.027	-0.033	0.043
DT8	0.868	0.655	0.274	0.876	0.666	0.260	-0.008	-0.012	0.014
DT9	0.974	0.780	0.232	0.965	0.766	0.245	0.008	0.014	-0.013
DT10	0.985	0.748	0.271	1.000	0.784	0.248	-0.015	-0.036	0.023
DT11	1.048	0.837	0.162	1.119	0.882	0.045	-0.071	-0.045	0.117
DT12	0.974	0.747	0.268	1.029	0.786	0.183	-0.055	-0.039	0.085
DT13	1.037	0.803	0.221	1.069	0.813	0.172	-0.032	-0.010	0.049
DT14	1.124	0.892	0.116	1.206	0.965	-0.017	-0.082	-0.073	0.133
DT15	1.173	0.946	0.095	1.242	0.974	-0.015	-0.069	-0.027	0.110
DT16	1.183	0.967	0.049	1.188	0.955	0.042	-0.005	0.012	0.008
DT17	1.120	0.924	0.097	1.175	0.934	0.007	-0.055	-0.010	0.090

Note: BP (Business performance); DT (I4.0 Digital technologies); RSME (Root mean squared error); MAE (Mean absolute error)

As a result, the findings revealed that I4.0 DT had a positive mediating influence on LMP and BP, thus proving the necessity of I4.0 DT to be implemented to solve the limitation faced by LMP. However, despite the difference in countries, the findings regarding the positive correlation between LMP and I4.0 DT as well as the direct positive effects of I4.0 DT towards BP exhibit similar verdicts with prior studies (Kamble et al., 2020; Tortorella and Fettermann, 2018).

Next, in contrast to the outcomes from Buer et al. (2021) revealing that LMP has a significant impact on operational performance when only digitalization occurs highly in that manufacturing firms although LMP contributed to operational performance individually, our findings differ and indicate that LMP itself can improve BP, which is persistent with prior studies regarding the capabilities of LMP in improving BP (Ng and Ghobakhloo, 2018; Shah and Ward, 2003). However, both our findings correspondingly indicated that the integration of both LMP and I4.0 DT will result in a greater improvement in achieving business excellence instead of implementing solely and these discoveries are coherent with prior studies done relating to this context (Rossini et al., 2019; Tortorella and Fettermann, 2018).

Moreover, with PLS-SEM capable of providing both knowledges of inherent consequences and prediction capabilities (Hair et al., 2016), the present research framework is regarded to be more competent as compared with prior studies due to its predictive power to predict future new cases and data (Shmueli et al., 2019). This will further increase the research framework's practicability by providing more appropriate managerial implications for future actions, and suitable to be adopted by researchers to conduct studies in their respective contexts.

In a nutshell, based on the comparison with prior studies, it can be established that the findings from this study although done in a different manner (i.e., country and approach) are robust in providing novel knowledge in literature, with both LMP and I4.0 DT are reiterated to be the significant domains in providing advancement in BP even in an emerging and developing country perspective regardless of manufacturing industries and both are vital to be implemented together.

5. Discussion

This paper reports the first attempt to narrow the literature gap by empirically examining the correlation among LMP, I4.0 DT, and BP by utilizing PLS-SEM to model their correlation. Numerous vital implications can be derived for academicians and practitioners as all four hypotheses were supported and justified.

5.1. Theoretical implication

This study will substantially advance the knowledge of I4.0 and LMP theoretically. Firstly, the authors proposed a new standpoint of recognizing the feasibility of executing I4.0 DT and LMP and corroborating with BP. Therefore, this will be the pioneer attempt that empirically studies the correlation thoroughly between I4.0 DT, LMP, and BP.

Next, this study will address the issue of I4.0 in Malaysia, a topic that has received little to no attention. Thus, this article will present a meaningful insight for researchers and academicians globally relating to the manufacturing environment in Malaysia, with the degree of application of both I4.0 and LMP in Malaysian manufacturing firms. The newfound insight is beneficial for academicians, experts, stakeholders, and governments as this allows them to comprehend better the scenario of the said context in emerging and developing countries in the Asia Pacific region, where the circumstances will significantly differ from those advance and developed nations. This is crucial as most empirical studies done previously are located in advanced nations (e.g., Germany and USA) (Kolberg and Zühlke, 2015; Kolberg et al., 2017; Sanders et al., 2016), where fundamental challenges faced by emerging and developing countries are not considered at all. Therefore, the findings enriched the literature by implying that both LMP and I4.0 DT had been successfully implemented in various stages in Malaysia and had reassured and confirmed the feasibility of implementation in emerging and developing countries.

The findings from this study revealed several massive implications and knowledge that will contribute significantly to the literature and successfully bridge the literature gap by providing profound insights that are still not present. The discoveries will be competent in unraveling the ambiguity and contradictory beliefs that plague researchers and academicians due to the lack of empirical data to support their perspectives. The findings of the positive direct effect of LMP on I4.0 DT provided a better understanding that LMP is vital to act as the foundation and prerequisite for I4.0 DT application in manufacturing firms. The finding is analogous and coherent with researchers claiming that LMPs are needed to act as the foundation in ensuring the successful implementation of I4.0 DT (Bortolotti et al., 2009; Buer et al., 2018; Nicoletti, 2013; Rüttimann and Stöckli, 2016; Sanders et al., 2017; Tortorella and Fettermann, 2018; Tortorella et al., 2019). Moreover, the findings of the study relating to the positive mediating effect and indirect effect of I4.0 DT on LMP and BP had empirically proven that with the resolution of accomplishing exceptional business excellence, I4.0 DT and LMP are essential to be integrated and implemented simultaneously to create an innovative hybrid manufacturing system instead of merely applying a sole approach. This finding is also coherent with several researchers stating the necessity of implementing and integrating both to achieve exceptional improvement in productivity, operational performance, etc. (Buer et al., 2018; Dombrowski et al., 2017; Mayr et al., 2018; Tortorella and Fettermann, 2018). Additionally, the positive and direct effect of I4.0 DT on BP is also proven empirically that implementing I4.0 DT can bring huge benefits and advantages to manufacturing firms that will eventually increase their performance. The finding of this positive effect is consistent with the perceived benefits and advantages stated by many researchers globally (Bédard-Maltais, 2017; Ghobakhloo and Fathi, 2019; Lee et al., 2017; Mohamed, 2018; Sony, 2018).

In addition, the proposed model developed, as shown in Fig. 1 in this study, is robust and suitable to be adopted and adapted by other researchers to conduct research in their preferable context as the model is proven to have medium out-of-sample prediction power by assessing the Q^2 value and PLSpredict. Lastly, this research can serve as a reference for researchers and academicians regarding the practicability of the methodology applied in the research, like applying PLS-SEM to model and analyze the correlation of I4.0 DT, LMP, and BP based on empirical data and the usage of electronic questionnaire for data collection.

5.2. Managerial implication

The outcomes of the present paper exhibited significant implications for practitioners and decision-makers relating to the implementation of LMP and I4.0. Furthermore, the study presented the long-awaited empirical evidence from manufacturing firms on the correlation of I4.0 DT and LMP and their association with BP. Finally, the confusion and ambiguity among practitioners and decision-makers regarding the compatibility of I4.0 DT and LMP will be resolved.

First and foremost, it has shown that Malaysia, an emerging and developing country is in various stages of implementing LMP and I4.0 DT and indeed not as claimed by a local newspaper article on the low implementation. This implied that the paradigm shifts of manufacturing towards I4.0 are no longer hype, similarly, stated by Kusiak (2019), and top management and decision-makers in Malaysia are well aware of their capabilities in ensuring corporate excellence. Hence, this is a wake-up call for others, especially SMEs, who must be mindful of such development and rapidly act by strategizing their implementation to ensure their corporate survival and sustainability.

Next, decision makers and top management facing tough competition and challenges should outline the strategy of applying both I4.0 DT and LMP in their manufacturing firms as results indicated that manufacturing firms, regardless of sizes, sales turnovers, and sectors, had successfully implemented both as well as obtained desirable improvement in BP. The previous study tends to focus on and argues that I4.0 DT and LMP are only viable to be implemented in large corporations, and SMEs will be the casualty (Sommer, 2015). However, this study has proven otherwise, where manufacturing sectors, sales turnovers, and company sizes are not the barriers hindering the implementation of I4.0 DT and LMP from gaining desirable advancement in BP.

Furthermore, this study discovered that organizations that tend to implement both LMP and I4.0 DT are the ones that are long-established. This is because most of the respondents who participated in the questionnaire originated from organizations established for more than 15 years. These findings are logical as the implementation cannot be done in a short timeframe where long-term planning is often needed, and implementation is always done in stages with a continuous improvement process (CIP), and optimization is often carried out upon it. Another factor is the high initial cost of investment and implementation of such approaches (Ghobakhloo and Fathi, 2019). Therefore, practitioners and decision-makers must be mindful that successive long-term planning is needed, and it is impossible to implement both rapidly and hope to obtain those perceived benefits in a short period. This is coherent with the saying, 'Rome was not built in a day.'

In addition, the results collected successfully demonstrated the direct positive effect of LMP and I4.0 DT on BP. Hence, it can be asserted that both LMP and I4.0 DT are competent in enhancing BP considerably (Bhamu and Sangwan, 2014). This discovery is consistent with previous studies as LMP is capable of reducing waste and improving productivity, and I4.0 DT is capable of real-time information sharing, improving flexibility to allow quick changes in firms with less reliance on workforces and creating a new business model that is not possible before (Sony, 2018). As a result, the findings can assure decision-makers and practitioners that it is feasible as well as one of the best methodologies to enhance performance by implementing both LMP and I4.0 DT.

Moreover, with the direct positive effect of LMP and I4.0 DT as well as I4.0 DT as the positive mediator for LMP and BP, this has substantiated that LMP is crucial for overcoming challenges in I4.0 DT implementation. Therefore, LMP must be the foundation and prerequisite for ensuring that manufacturing firms are ready for I4.0 DT implementation. This is due to the capabilities of LMP to effectively and systematically reduce waste and create a culture of continuous improvement, empowering employees, standardization, etc. (Bhamu and Sangwan, 2014). Hence, similarly to what Bortolotti et al. (2009) and Nicoletti (2013) claimed, it is vital to improve the efficiency of an operation via LMP first and undergo digitalization with I4.0 DT, as digitalizing an unproductive or chokepoint process will still be similar after implementing I4.0 DT. In short, practitioners and decision-makers should be aware that the presence of I4.0 DT will alter the nature of LMP and LMP itself will work as the foundation guiding the implementation of I4.0 DT. Thus, they must be prepared and open to new changes.

Subsequently, although the findings illustrate that implementing LMP has a direct and positive effect on BP, the effects are greatly amplified with I4.0 DT as the mediating variable. Hence, it is inherent that solely implementing either is unable to achieve substantial improvement in BP compared to executing and integrating both approaches. Hence, I4.0 DT is vital to be implemented to further upgrade the system and process of that manufacturing firms by experiencing digitalization upon existing LMP. Furthermore, the capabilities of I4.0 DT have enabled new characteristics for manufacturing firms based on its design principles, which were not achievable in the past (Ghobakhloo, 2018). The findings also proved that LMP had fundamentally met its threshold and I4.0 DT must be implemented to further improve LM maturity as well as solve the shortcomings and impediments faced in executing LMP, which is consistent with numerous studies done previously (Buer et al., 2018; Kolberg and Zühlke, 2015; Rüttimann and Stöckli, 2016; Tortorella and Fettermann, 2018).

Last but not least, decision-makers, practitioners, and top management must understand the importance and capabilities of both I4.0 DT and LMP and strive to achieve the right balance. Thus, with the identification of a positive correlation between LMP, I4.0 DT, and BP, as well as the positive mediating effect of I4.0 DT on LMP and BP, it provided more profound insights and arguments for better developing a comprehensive strategy for improving and enhancing their respective manufacturing firms, with integrating LMP into their organizational culture and I4.0 DT in a collective way creating a new robust hybrid system that is unique to the respective manufacturing firm. This will significantly reduce the risk associated with implementing I4.0 DT and LMP in their respective firms, as the growth in BP with both approaches was proven empirically. Hence, the findings are also vital as it has reassured practitioners and decision-makers that implementing I4.0 DT and LMP simultaneously in an emerging and developing nation is relevant and feasible. However, the challenges met, like lack of resources and skilled workers, will be more severe than advanced nations.

6. Conclusion

This study successfully confirmed all four hypotheses and created a framework that mapped the correlation of LMP, I4.0 DT, and BP. The empirical data was effectively compiled from 124 respondents from 124 different manufacturing firms in Malaysia. The data, with the help of an electronic questionnaire, were analyzed via the PLS-SEM modeling technique with SmartPLS software. The study's implication confirmed that LMP and I4.0 DT have a direct positive correlation on BP, and I4.0 DT as the mediator acts significantly well for LMP and BP. Moreover, it is also proven that there is a positive and direct correlation between LMP and I4.0 DT. Hence, practitioners and decision-makers must be aware and prepared for this shift in manufacturing industries to ensure they can prevail in these difficult times.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Ante G, Facchini F, Mossa G, and Digiesi S (2018). Developing a key performance indicators tree for lean and smart production systems. IFAC-PapersOnLine, 51(11): 13-18. https://doi.org/10.1016/j.ifacol.2018.08.227

Bagozzi RP and Yi Y (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16: 74-94. https://doi.org/10.1007/BF02723327

Becker JM, Klein K, and Wetzels M (2012). Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models. Long Range Planning, 45(5-6): 359-394. https://doi.org/10.1016/j.lrp.2012.10.001

Becker JM, Ringle CM, Sarstedt M, and Völckner F (2015). How collinearity affects mixture regression results. Marketing Letters, 26(4): 643-659. https://doi.org/10.1007/s11002-014-9299-9

Bédard-Maltais PO (2017). Industry 4.0: The new industrial revolution: Are Canadian manufacturers ready? Business Development Bank of Canada, Toronto, Canada.

Bhamu J and Sangwan KS (2014). Lean manufacturing: Literature review and research issues. International Journal of Operations and Production Management, 34(7): 876-940. https://doi.org/10.1108/IJOPM-08-2012-0315

Bittencourt VL, Alves AC, and Leão CP (2019). Lean thinking contributions for Industry 4.0: A systematic literature review. IFAC-PapersOnLine, 52(13): 904-909. https://doi.org/10.1016/j.ifacol.2019.11.310

Bittencourt VL, Alves AC, and Leão CP (2021). Industry 4.0 triggered by lean thinking: Insights from a systematic literature review. International Journal of Production Research, 59(5): 1496-1510. https://doi.org/10.1080/00207543.2020.1832274

Bortolotti T, Romano P, and Nicoletti B (2009). Lean first, then automate: An integrated model for process improvement in pure service-providing companies. In the IFIP International Conference on Advances in Production Management Systems, Springer, Heidelberg, Germany: 579-586. https://doi.org/10.1007/978-3-642-16358-6_72

Buer SV, Semini M, Strandhagen JO, and Sgarbossa F (2021). The complementary effect of lean manufacturing and digitalization on operational performance. International Journal of Production Research, 59(7): 1976-1992. https://doi.org/10.1080/00207543.2020.1790684

Buer SV, Strandhagen JO, and Chan FT (2018). The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda. International Journal of Production Research, 56(8): 2924-2940. https://doi.org/10.1080/00207543.2018.1442945

Byrne BM (2013). Structural equation modeling with EQS: Basic concepts, applications, and programming. Routledge, New York, USA. https://doi.org/10.4324/9780203807644

Byrne BM (2016). Structural equation modeling with Amos: Basic concepts, applications, and programming. Routledge, New York, USA. https://doi.org/10.4324/9781315757421

Cheah JH, Ting H, Ramayah T, Memon MA, Cham TH, and Ciavolino E (2019). A comparison of five reflective–formative estimation approaches: Reconsideration and recommendations for tourism research. Quality and Quantity, 53(3): 1421-1458. https://doi.org/10.1007/s11135-018-0821-7

Cohen J (1988). Statistical power analysis for the behavioral sciences. Lawrence Erlbaum Associates, New York, USA.

Davies R, Coole T, and Smith A (2017). Review of socio-technical considerations to ensure successful implementation of Industry 4.0. Procedia Manufacturing, 11: 1288-1295. https://doi.org/10.1016/j.promfg.2017.07.256

Dombrowski U, Richter T, and Krenkel P (2017). Interdependencies of Industry 4.0 and lean production systems: A use cases analysis. Procedia Manufacturing, 11: 1061-1068. https://doi.org/10.1016/j.promfg.2017.07.217

Ejsmont K and Gładysz B (2020). Lean Industry 4.0-Wastes versus technology framework. In The 10th International Conference on Engineering, Project, and Production Management, Springer, Singapore, Singapore: 537-546. https://doi.org/10.1007/978-981-15-1910-9_44

Faul F, Erdfelder E, Buchner A, and Lang AG (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41(4): 1149-1160. https://doi.org/10.3758/BRM.41.4.1149 **PMid:19897823**

Faul F, Erdfelder E, Lang AG, and Buchner A (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behavior Research Methods, 39(2): 175-191. https://doi.org/10.3758/BF03193146 **PMid:17695343**

Fornell C and Larcker DF (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1): 39-50. https://doi.org/10.1177/002224378101800104

Garza-Reyes JA (2015). Lean and green–A systematic review of the state of the art literature. Journal of Cleaner Production, 102: 18-29. https://doi.org/10.1016/j.jclepro.2015.04.064

Geisser S (1974). A predictive approach to the random effect model. Biometrika, 61(1): 101-107. https://doi.org/10.1093/biomet/61.1.101

Ghobakhloo M (2018). The future of manufacturing industry: A strategic roadmap toward Industry 4.0. Journal of Manufacturing Technology Management, 29(6): 910-936. https://doi.org/10.1108/JMTM-02-2018-0057

Ghobakhloo M and Ching NT (2019). Adoption of digital technologies of smart manufacturing in SMEs. Journal of Industrial Information Integration, 16: 100107. https://doi.org/10.1016/j.jii.2019.100107

Ghobakhloo M and Fathi M (2019). Corporate survival in Industry 4.0 era: The enabling role of lean-digitized manufacturing. Journal of Manufacturing Technology Management, 31(1): 1-30. https://doi.org/10.1108/JMTM-11-2018-0417

Hair JF, Black WC, Babin BJ, and Anderson RE (2009). Multivariate data analysis. 7th Edition, Prentice Hall, Upper Saddle River, USA.

Hair JF, Hult GTM, Ringle CM, and Sarstedt M (2016). A primer on partial least squares structural equation modeling (PLS-SEM). SAGE Publications, Thousand Oaks, USA.

Hair JF, Matthews LM, Matthews RL, and Sarstedt M (2017a). PLS-SEM or CB-SEM: Updated guidelines on which method to use.

International Journal of Multivariate Data Analysis, 1(2): 107-123. https://doi.org/10.1504/IJMDA.2017.10008574

Hair JF, Sarstedt M, and Ringle CM (2019). Rethinking some of the rethinking of partial least squares. European Journal of Marketing, 53(4): 566-584. https://doi.org/10.1108/EJM-10-2018-0665

Hair JF, Sarstedt M, Ringle CM, and Gudergan SP (2017b). Advanced issues in partial least squares structural equation modeling. SAGE Publications, Mobile, USA. https://doi.org/10.1007/978-3-319-05542-8_15-1

Imran M, Hameed WU, and Haque AU (2018). Influence of Industry 4.0 on the production and service sectors in Pakistan: Evidence from textile and logistics industries. Social Sciences, 7(12): 246. https://doi.org/10.3390/socsci7120246

Kamble S, Gunasekaran A, and Dhone NC (2020). Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies. International Journal of Production Research, 58(5): 1319-1337. https://doi.org/10.1080/00207543.2019.1630772

Kline RB (2015). Principles and practice of structural equation modeling. Guilford Press, New York, USA.

Klingenberg CO, Borges MAV, and do Vale Antunes JrJA (2022). Industry 4.0: What makes it a revolution? A historical framework to understand the phenomenon. Technology in Society, 70: 102009. https://doi.org/10.1016/j.techsoc.2022.102009

Kock N and Lynn G (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. Journal of the Association for Information Systems, 13(7): 1-40. https://doi.org/10.17705/1jais.00302

Kolberg D and Zühlke D (2015). Lean automation enabled by Industry 4.0 technologies. IFAC-PapersOnLine, 48(3): 1870-1875. https://doi.org/10.1016/j.ifacol.2015.06.359

Kolberg D, Knobloch J, and Zühlke D (2017). Towards a lean automation interface for workstations. International Journal of Production Research, 55(10): 2845-2856. https://doi.org/10.1080/00207543.2016.1223384

Kusiak A (2019). Fundamentals of smart manufacturing: A multi-thread perspective. Annual Reviews in Control, 47: 214-220. https://doi.org/10.1016/j.arcontrol.2019.02.001

Lee MX, Lee YC, and Chou CJ (2017). Essential implications of the digital transformation in Industry 4.0. Journal of Scientific and Industrial Research, 76(8): 465-467.

Liker JK (2004). The Toyota way: 14 management principles from the world's greatest manufacturer. McGraw-Hill Education, New York, USA.

Ma J, Wang Q, and Zhao Z (2017). SLAE–CPS: Smart lean automation engine enabled by cyber-physical systems technologies. Sensors, 17(7): 1500. https://doi.org/10.3390/s17071500 **PMid:28657577 PMCid:PMC5539867**

Mardia KV (1970). Measures of multivariate skewness and kurtosis with applications. Biometrika, 57(3): 519-530. https://doi.org/10.1093/biomet/57.3.519

Mayr A, Weigelt M, Kühl A, Grimm S, Erll A, Potzel M, and Franke J (2018). Lean 4.0-A conceptual conjunction of lean management and Industry 4.0. Procedia CIRP, 72: 622-628. https://doi.org/10.1016/j.procir.2018.03.292

MITI (2018). Industry 4WRD: National policy on Industry 4.0. Ministry of International Trade and Industry, Kuala Lumpur, Malaysia.

Mohamed M (2018). Challenges and benefits of Industry 4.0: An overview. International Journal of Supply and Operations Management, 5(3): 256-265.

Mrugalska B and Wyrwicka MK (2017). Towards lean production in Industry 4.0. Procedia Engineering, 182: 466-473. https://doi.org/10.1016/j.proeng.2017.03.135

Nawanir G (2016). The effect of lean manufacturing on operations performance and business performance in manufacturing companies in Indonesia. Universiti Utara Malaysia, Kedah, Malaysia.

Ng TC and Ghobakhloo M (2018). What determines lean manufacturing implementation? A CB-SEM model. Economies, 6(1): 9. https://doi.org/10.3390/economies6010009

Nicoletti B (2013). Lean and automate manufacturing and logistics. In the IFIP International Conference on Advances in Production Management Systems, Springer, Heidelberg, Germany: 278-285. https://doi.org/10.1007/978-3-642-41263-9_34

Nunnally JC and Bernstein IH (1995). Psychometric theory. McGraw-Hill, New York, USA.

Ohno T (2019). Toyota production system: Beyond large-scale production. Productivity Press, Tokyo, Japan. https://doi.org/10.4324/9780429273018

Pereira AC, Dinis-Carvalho J, Alves AC, and Arezes P (2019). How Industry 4.0 can enhance lean practices. FME Transactions, 47(4): 810-822. https://doi.org/10.5937/fmet1904810P

Podsakoff PM, MacKenzie SB, Lee JY, and Podsakoff NP (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5): 879-903. https://doi.org/10.1037/0021-9010.88.5.879 **PMid:14516251**

Powell D, Romero D, Gaiardelli P, Cimini C, and Cavalieri S (2018). Towards digital lean cyber-physical production systems: Industry 4.0 technologies as enablers of leaner production. In the IFIP International Conference on Advances in Production Management Systems, Springer, Seoul, Korea: 353-362. https://doi.org/10.1007/978-3-319-99707-0_44

Preacher KJ and Hayes AF (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. Behavior Research Methods, Instruments, and Computers, 36(4): 717-731. https://doi.org/10.3758/BF03206553 **PMid:15641418**

Preacher KJ and Hayes AF (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3): 879-891. https://doi.org/10.3758/BRM.40.3.879 **PMid:18697684**

Prinz C, Kreggenfeld N, and Kuhlenkötter B (2018). Lean meets Industrie 4.0–A practical approach to interlink the method world and cyber-physical world. Procedia Manufacturing, 23: 21-26. https://doi.org/10.1016/j.promfg.2018.03.155

Ramayah TJFH, Cheah J, Chuah F, Ting H, and Memon MA (2018). Partial least squares structural equation modeling (PLS-SEM) using smartPLS 3.0: An updated guide and practical guide to statistical analysis. Pearson, Kuala Lumpur, Malaysia.

Ringle CM, Wende S, and Becker JM (2015). SmartPLS 3. SmartPLS GmbH, Boenningstedt. Journal of Service Science and Management, 10(3): 32-49.

Rojko A (2017). Industry 4.0 concept: Background and overview. International Journal of Interactive Mobile Technologies, 11(5): 77-90. https://doi.org/10.3991/ijim.v11i5.7072

Rossini M, Costa F, Tortorella GL, and Portioli-Staudacher A (2019). The interrelation between Industry 4.0 and lean production: An empirical study on European manufacturers. The International Journal of Advanced Manufacturing Technology, 102(9): 3963-3976. https://doi.org/10.1007/s00170-019-03441-7

Rüttimann BG and Stöckli MT (2016). Lean and Industry 4.0-Twins, partners, or contenders? A due clarification regarding the supposed clash of two production systems. Journal of Service Science and Management, 9(6): 485-500. https://doi.org/10.4236/jssm.2016.96051

Sanders A, Elangeswaran C, and Wulfsberg JP (2016). Industry 4.0 implies lean manufacturing: Research activities in Industry 4.0 function as enablers for lean manufacturing. Journal of Industrial Engineering and Management, 9(3): 811-833. https://doi.org/10.3926/jiem.1940

Sanders AK, Subramanian KR, Redlich T, and Wulfsberg JP (2017). Industry 4.0 and lean management–synergy or contradiction? In the IFIP International Conference on Advances in Production Management Systems, Springer, Hamburg, Germany: 341-349. https://doi.org/10.1007/978-3-319-66926-7_39

Santos C, Mehrsai A, Barros AC, Araújo M, and Ares E (2017). Towards Industry 4.0: An overview of European strategic roadmaps. Procedia Manufacturing, 13: 972-979. https://doi.org/10.1016/j.promfg.2017.09.093

Sarstedt M, Hair JrJF, Cheah JH, Becker JM, and Ringle CM (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. Australasian Marketing Journal, 27(3): 197-211. https://doi.org/10.1016/j.ausmj.2019.05.003

Sarstedt M, Ringle CM, and Hair JF (2022). Partial least squares structural equation modeling. In: Homburg C, Klarmann M, and Vomberg A (Eds.), Handbook of market research: 587-632. Springer, Munich, Germany. https://doi.org/10.1007/978-3-319-57413-4_15

Satoglu S, Ustundag A, Cevikcan E, and Durmusoglu MB (2018). Lean transformation integrated with Industry 4.0 implementation methodology. In the Industrial Engineering in the Industry 4.0 Era, Springer, Vienna, Austria: 97-107. https://doi.org/10.1007/978-3-319-71225-3_9

Schmidt R, Möhring M, Härting RC, Reichstein C, Neumaier P, and Jozinović P (2015). Industry 4.0-potentials for creating smart products: Empirical research results. In the International Conference on Business Information Systems, Springer, Poznan, Poland: 16-27. https://doi.org/10.1007/978-3-319-19027-3_2

Shah R and Ward PT (2003). Lean manufacturing: Context, practice bundles, and performance. Journal of Operations Management, 21(2): 129-149. https://doi.org/10.1016/S0272-6963(02)00108-0

Shah R and Ward PT (2007). Defining and developing measures of lean production. Journal of Operations Management, 25(4): 785-805. https://doi.org/10.1016/j.jom.2007.01.019

Sharma PN, Shmueli G, Sarstedt M, Danks N, and Ray S (2021). Prediction-oriented model selection in partial least squares path modeling. Decision Sciences, 52(3): 567-607. https://doi.org/10.1111/deci.12329

Shmueli G, Ray S, Estrada JMV, and Chatla SB (2016). The elephant in the room: Predictive performance of PLS models. Journal of Business Research, 69(10): 4552-4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Shmueli G, Sarstedt M, Hair JF, Cheah JH, Ting H, Vaithilingam S, and Ringle CM (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11): 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189

Sommer L (2015). Industrial revolution-Industry 4.0: Are German manufacturing SMEs the first victims of this revolution? Journal of Industrial Engineering and Management, 8(5): 1512-1532. https://doi.org/10.3926/jiem.1470

Sony M (2018). Industry 4.0 and lean management: A proposed integration model and research propositions. Production and Manufacturing Research, 6(1): 416-432. https://doi.org/10.1080/21693277.2018.1540949

Stone M (1974). Cross-validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society: Series B (Methodological), 36(2): 111-133. https://doi.org/10.1111/j.2517-6161.1974.tb00994.x

Strandhagen JW, Alfnes E, Strandhagen JO, and Vallandingham LR (2017). The fit of Industry 4.0 applications in manufacturing logistics: A multiple case study. Advances in Manufacturing, 5(4): 344-358. https://doi.org/10.1007/s40436-017-0200-y

Szász L, Demeter K, Rácz BG and Losonci D (2020). Industry 4.0: A review and analysis of contingency and performance effects. Journal of Manufacturing Technology Management, 32(3): 667-694. https://doi.org/10.1108/JMTM-10-2019-0371

Tortorella G, Sawhney R, Jurburg D, de Paula IC, Tlapa D, and Thurer M (2021). Towards the proposition of a lean automation framework: Integrating Industry 4.0 into lean production. Journal of Manufacturing Technology Management, 32(3): 593-620. https://doi.org/10.1108/JMTM-01-2019-0032

Tortorella GL and Fettermann D (2018). Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies. International Journal of Production Research, 56(8): 2975-2987. https://doi.org/10.1080/00207543.2017.1391420

Tortorella GL, Giglio R, and Van Dun DH (2019). Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement. International Journal of Operations and Production Management, 39(6/7/8): 860-886. https://doi.org/10.1108/IJOPM-01-2019-0005

Vogel-Heuser B and Hess D (2016). Guest editorial Industry 4.0–Prerequisites and visions. IEEE Transactions on Automation Science and Engineering, 13(2): 411-413. https://doi.org/10.1109/TASE.2016.2523639

Wagner T, Herrmann C, and Thiede S (2017). Industry 4.0 impacts on lean production systems. Procedia CIRP, 63: 125-131. https://doi.org/10.1016/j.procir.2017.02.041

Womack JP and Jones DT (1997). Lean thinking-Banish waste and create wealth in your corporation. Journal of the Operational Research Society, 48(11): 1148-1148. https://doi.org/10.1038/sj.jors.2600967

Wong KKK (2019). Mastering partial least squares structural equation modeling (PLS-Sem) with Smartpls in 38 Hours. iUniverse, Bloomington, USA.