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Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies

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The current literature claims the direct effects of industry 4.0 technologies (I4 T) on lean manufacturing practices (LMP) and sustainable organisational performance (SOP). LMP are also found to have a positive influence on SOP. However, the integrated effect of I4 T and LMP on SOP has not been empirically investigated. To address this gap, this research study investigates the indirect effects of I4 T on SOP with LMP as the mediating variable; furthermore, it aims to confirm or not the direct effects of I4 T on LMP and SOP. The study is based on data collected from 205 managers, working in 115 manufacturing firms. The findings suggest significant direct and indirect effects of I4 T on SOP and confirm the presence of LMP as a strong mediating variable. The results of the study extend the literature on I4 T by identifying I4 T as an enabler of LMP, leading to enhancement of the SOP. Implications and future research directions for academicians, practitioners, and consultants are provided.

Keywords: industry 4.0; lean manufacturing; sustainability; organisational performance; manufacturing companies

1. Introduction

The intensified competition in supply chains has pushed organisations to update their manufacturing systems to a smart level. In a smart manufacturing system, the manufacturing processes are more flexible, intelligent, and agile, and are well equipped to meet the challenges of a dynamic and global market (Shen and Norrie 1999; Zhong et al. 2017). Industry 4.0 and its synonyms, such as smart and intelligent manufacturing, drive the existing manufacturing systems toward the development of an open, digital, automated, and intelligent manufacturing platform for industrial-networked information application (Kamble, Gunasekaran, and Sharma 2018; Vaidya, Ambad, and Bhosle 2018). An Industry 4.0 manufacturing environment in a value chain ensures the availability of all the physical processes and information flows to the connected partners in real-time (Wang, Wan et al. 2016). Industry 4.0 technologies (I4 T) contribute to the manufacturing organisations in achieving sustainable goals through improved work environment, employee morale, reduced lead time, customised products, and improved product quality (Kamble, Gunasekaran, and Gawankar 2018). I4 T are identified as significant initiatives for manufacturing supply chains in emerging economies for achieving ecological, social, and economic sustainability (Luthra and Mangla 2018; Stock and Seliger 2016). Key I4 T that hold potential value for sustainable organisational performance (SOP) are listed in Table 1.

Lean is defined as 'a set of management principles and techniques geared towards eliminating waste in the manufacturing process and increasing the flow of activities that, from the customers' perspective, add value to the product' (Taj 2008; Womack and Jones 1996). Lean manufacturing practices (LMP) are a combination of techniques deployed for productivity improvement and reduction in manufacturing costs (Sanders, Elangeswaran, and Wulfsberg 2016), reduced environmental impacts (Chiarini 2014; Torielli et al. 2011), and increased social sustainability (de Freitas, Costa, and Ferraz 2017; Wong and Wong 2014). As the LMP are associated with bringing improvement in the processes, they facilitate achieving sustainable supply chain and organisational performance (Azevedo et al. 2012; Das 2018; Kitchen 2005; Sajan et al. 2017; Tamás and Illés 2016; Wu et al. 2015). The literature identifies that issues in LMP implementation may be addressed by using suitable information and communication technology applications (Buer, Strandhagen, and Chan 2018). The various I4 T act as integrated solutions that align with the lean thinking objectives of an organisation. Both I4 T and LMP are aimed at improving SOP (Cherrafi et al. 2017; de Freitas, Costa, and Ferraz 2017; Kang et al. 2016; Luthra and Mangla 2018; Quezada

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Table 1. Industry 4.0 technologies.

Purpose	Industry 4.0 technologies	Sources
Smart data collection, storage, analysis, and sharing technologies	Big data analytics (BDA), cloud computing (CC), Internet of things (IoT) and sensors, simulation, and prototyping.	Li et al. (2017), Lin et al. (2016), Yang et al. (2017), Bahrin et al., (2016), Stock and Seilger, (2016), Rüßmann et al. (2015), Wang, Zhu et al. (2016), Yu et al. (2017)
Shop floor technologies	Additive manufacturing (AM), virtual reality (VR), augmented reality (AR), IoT, sensors, and robotic systems (RS).	
Integration technologies	Cyber-physical systems (CPS) and cyber-security systems (CSS).	

et al. 2017; Stock and Seliger 2016). Operational excellence towards sustainable development goals through Industry 4.0. Integration of I4 T and LMP will not only expedite the development of lean systems in manufacturing organisations but also reduce the perceived risk associated with the high implementation costs of I4 T (Kolberg and Zühlke 2015). The integration of I4 T and LMP offers lucrative cost-saving benefits in areas where it is difficult to implement simple lean techniques. There are few studies available in the literature that indicate a positive relationship between the I4 T and LMP (Sanders, Elangeswaran, and Wulfsberg 2016; Tortorella and Fettermann 2018; Wagner, Herrmann, and Thiede 2017). However, these studies lack information on how I4 T can enable the successful implementation of LMP, and how the integration of I4 T and LMP will influence SOP (Buer, Strandhagen, and Chan 2018). Furthermore, to the best of our knowledge, there are no studies in the literature that empirically investigate the relationship between I4 T, LMP, and SOP. The present study is undertaken to address this gap in the literature. We draw on the emerging literature of I4 T, LMP, and SOP to develop and validate a research model that investigates the relationship between the I4 T, LMP, and SOP. More specifically, the research aims to achieve the following objectives:

(1) To confirm or not the effects of I4 T on LMP and of I4 T on SOP, and
(2) To investigate the integrated effect of I4 T and LMP on SOP.

The information for the above research questions was obtained through a sample survey conducted on 205 industry practitioners drawn from 115 Indian manufacturing organisations. The remainder of the paper is organised as follows: section 2 presents the theoretical background and proposed research model. Section 3 discusses the research methodology adopted in this study. Section 4 presents the results and discussions. The conclusions, implications, and limitations of the study are presented in section 5.

2. Theoretical background

2.1. Industry 4.0 technologies

Industry 4.0 refers to the digital manufacturing system provided by the successful integration of production processes, information technologies, and techniques. The primary objective of industry 4.0 is to improve the efficiency and responsiveness of the manufacturing system (Ahuett-Garza and Kurfess 2018). The I4 T operates on the principles of horizontal and vertical integration of manufacturing systems (Fatorachian and Kazemi 2018) and are driven by real-time data interchange between the various partners in the manufacturing value chain (Li et al. 2017; Thoben et al. 2014). The IoT, BDA, AM, RS, AR, CC, and CPS are identified as the significant I4 T that enhance the process integration, leading to improved SOP (Kamble, Gunasekaran, and Gawankar 2018; Liao et al. 2017). The CPS, CC, and IoT are the core information technology components of Industry 4.0. The CPS refers to the integration between the various physical systems, such as CNC, milling machine, lathe machine, and other equipment, and a central processing unit (e.g. a computer system) that makes the entire arrangement in the factory adaptable (Ivanov et al. 2016; Karakose and Yetis 2017; Monostori 2014). The CC is a third-party service provider for the storage of data or a database on the Internet. The cloud is based at a remote location, not at the site where the manufacturing activities are performed (Liu and Xu 2017). The CC offers the benefits of economies of operation, improved speed of service, and easy accessibility (Yu et al. 2017). The IoT brings the interaction between the machines without any human intervention (Da Xu, He, and Li 2014). IoT uses a network of devices, with each device having its unique identification to the connected computer system. The IoT-controlled manufacturing systems are smart, as they can remotely control all the connected devices with high accuracy and efficiency (Lee, Yoon, and Kim 2017; Lu and Cecil 2016). I4T-enabled production systems generate massive amounts of data and require specialised data collection, storage, analysis, and sharing technologies. BDA refers to the real-time data collection, use of analytical tools, and computer algorithms for deriving meaningful insights and patterns for improved decision-making (Jeble et al. 2018; LaValle et al. 2011). BDA contributes to achieving sustainable business performance and competitive advantage (Wamba et al. 2017). Manufacturing organisations are extensively using BDA (Lee, Yoon, and Kim 2017; Qian, Zhong, and Du 2017; Yuan, Qin, and Zhao 2017) and are required to develop their BDA capability to exploit the benefits of virtual manufacturing systems (Moyne and Iskandar 2017; Reis and Gins 2017).

AM, AR, and RS refer to the use of technology on the shop floor for making the manufacturing process simpler, safer, and more efficient for attaining sustainable objectives. In AM, a three-dimensional digital model is generated with the use of computer-aided design software followed by forming the final product using a 3D printer (Oesterreich and Teuteberg 2016). AM contributes to industry 4.0 objectives by manufacturing customised products in small batches, producing sophisticated and lightweight designs with a high level of accuracy (Rüßmann et al. 2015; Stock and Seliger 2016). Though in a nascent stage of adoption, AR is becoming famous for creating an interactive experience of the real world. The AR augments real-world objects using computer-generated perceptual information (Schueffel 2017). AR-based applications using smart glasses and smartphone technologies are found to improve the efficiency of industrial robot-driven production cells (Malý, Sedláček, and Leitao 2016). AR plays a significant role in performing complex duties involved in maintenance, locating devices and spare parts in the warehouse, and executing critical instructions over mobile phones (Paelke 2014). Other potential areas for the application of AR include quality control, remote assistance, logistics, safety management, and employee training (Pierdicca et al. 2017). The use of RS in manufacturing organisations provides a high level of autonomy, flexibility, and cooperation on the shop floors, and are expected to start interacting with one another, helping the human workers perform delicate and unsafe tasks with high levels of precision and safety (Bahrin et al. 2016; Rüßmann et al. 2015).

Nonetheless, implementing I4 T is not devoid of limitations. Even though I4 T can quickly adjust to the manufacturing environments, the implementation process and the adjustment goals are controlled by humans, which acts as a major barrier (Carvalho et al. 2018). In the literature, I4 T are predicted to contribute to the sustainable objectives of the organisation (Carvalho et al. 2018; Kamble, Gunasekaran, and Gawankar 2018; Lin et al. 2018; Luthra and Mangla 2018; Tortorella and Fettermann 2018; Zhong et al. 2017).

2.2. Lean manufacturing practices

The main thrust of LMP is to have a streamlined process flow so that products are manufactured as per the requirements of the customers with little or no waste (Shah and Ward 2003; Vinodh and Joy 2012). Shah and Ward (2007) identified ten dimensions of LMP, as shown in Table 2.

Sanders, Elangeswaran, and Wulfsberg (2016) classified these ten LMP dimensions into four factors: supplier factors (SF, JIT, and SD), process factors (PS, CF, and STR), control and human factors (TPM, SPC, and EI), and customer factor (CI). In the present study, all ten LMP dimensions were considered for analysis. The supplier factor is concerned with the flow of products and information between the supplier and organisation and is aimed at integrating the existing suppliers

Table 2. Dimension of lean manufacturing practices.

LMP Dimension	Definition
Supplier feedback (SF)	This refers to the performance feedback received from the customers that is communicated back to the suppliers.
Just-In-Time (JIT)	This refers to the supply of products by the suppliers in the specified quantity, at a specified time and specified location.
Supplier development (SD)	This refers to the matching of supplier and manufacturer competency levels.
Customer involvement (CI)	This refers to understanding customer needs and satisfying them.
Pull systems (PS)	This refers to the initiation of the production schedules by the succeeding department or customers through Kanban, rather than the manufacturer initiating the production by himself.
Continuous flow (CF)	This refers to the streamlined flow of products without significant breaks and downtime.
Setup time reduction (STR)	This refers to the reduction of the setup time before starting the production so that the process adapts to the variations in the resources.
Total productive/preventive maintenance (TPM)	This refers to avoiding machine and equipment breakdowns through active maintenance schedules and procedures.
Statistical process control (SPC)	This refers to the development of a high-quality culture where the defects from one process should not get percolated to the subsequent operations.
Employee involvement (EI)	This refers to the commitment, participation, and empowerment of the employees toward the development of the organisation.

with the business processes. The process factors are aimed to develop an efficient lean manufacturing system and are concerned with the smooth flow of the raw materials into the transformation process and their conversion to finished goods. The control and human factors ensure the production of quality goods, which is an outcome of the successful integration of the health of the manufacturing equipment, statistical process control, and human involvement. In an industry 4.0 environment, the employees must be trained and empowered to take corrective action based on real-time information received through various sources, and therefore are included as an important component of this factor. The customer factor ensures that the product and service offerings provide customer satisfaction. The LMP supports the manufacturing organisations in becoming strong contenders in the highly competitive global markets (Alhuraish, Robledo, and Kobi 2017; Nyambu 2017). Lean implementation in manufacturing organisations is found to improve resource utilisation by 30% to 70% by eliminating different types of waste (Nallusamy 2016). Many manufacturing companies still struggle to transform themselves into lean organisations (Jadhav, Mantha, and Rane 2014). This failure is attributed to an inappropriate implementation environment (Azadegan et al. 2013), a lack of lean tools and techniques meeting the operational requirements (Kolberg and Zühlke 2015), and the inability of the firms to sustain the initial momentum provided by the success of lean implementation (Netland 2016).

2.3. *Sustainable organizational performance*

The various stakeholders of an organisation, such as the suppliers, government agencies, customers, and competitors, have different expectations from the organisations that cannot be met by pursuing single goals (Zhu, Sarkis, and Lai 2012). In order to satisfy the varying needs of all the stakeholders, the organisations are required to perform on three sustainable dimensions: economic, environmental, and social, which are together referred to as the triple bottom line (TBL) (Elkington 1998). TBL is acknowledged to be the best measure for evaluating the sustainable performance of an organisation (Gimenez, Sierra, and Rodon 2012). Zhu, Geng, and Lai (2011) used economic and environmental performance dimensions to measure organisational performance. The effect of lean management principles can be best measured on all three sustainability dimensions of organisational performance (Sajan et al. 2017). In the context of an industry 4.0 environment, various I4 T is found to have a positive effect on the sustainable performance of the organisations. However, the literature lacks empirical support validating the impact of I4 T on SOP in different industries (Kamble, Gunasekaran, and Gawankar 2018). Therefore, in this study we consider economic performance (EP), environmental performance (EVP) and social performance (SP) as the dimensions of SOP.

2.4. *Industry 4.0 and lean manufacturing practices*

LMP offers huge potential to implement innovative automation technologies in manufacturing (Kolberg and Zühlke 2015). It is claimed that I4 T support manufacturing organisations to overcome the barriers of lean implementation (Sanders, Elangeswaran, and Wulfsberg 2016). The real-time information provided by I4 T is found to be very useful in preparing accurate value stream maps, which are considered the first step in the LMP implementation process (Chen and Chen 2014; Meudt, Metternich, and Abele 2017). A value stream map is used for mapping a series of activities that take a product or service from its initial stage through to the customer. These maps are used for analysing the current problems and designing a future state with reduced lean waste (Rother and Shook 1999). The I4 T are claimed to have a positive influence on the LMP (Sanders, Elangeswaran, and Wulfsberg 2016; Tortorella and Fettermann 2018).

2.5. *Industry 4.0 and sustainable organisational performance*

I4 T is expected to play a significant role in moving social and industrial organisations toward sustainable development (de Sousa Jabbour et al. 2018). I4 T facilitates achieving a high level of process integration, leading to improvement in organisational performance on all three sustainability dimensions (Kamble, Gunasekaran, and Gawankar 2018). On the economic dimension, I4 T contributes strongly on value creation, manufacturing flexibility, and product customisation, leading to increased customer satisfaction (Kagermann et al. 2013; Lasi et al. 2014; Stock and Seliger 2016). The automation and digitisation features of I4 T drive the manufacturing organisations toward reduced lead times, lower manufacturing costs, and superior quality (Oesterreich and Teuteberg 2016; Ramadan, Al-Maimani, and Noche 2017). In the environmental dimension, the real-time information gathered from different value chain partners helps the organisations allocate their manufacturing resources, such as materials, energy, water, and products, efficiently (de Sousa Jabbour et al. 2018; Stock and Seliger 2016). I4 T also supports the reduction of greenhouse gas emissions (Peukert et al. 2015), energy consumption (Herrmann et al. 2014; Karnouskos et al. 2009), and inventory levels of raw material; efficient capacity utilisation (Wang, Wan et al. 2016; Wang, Zhu et al. 2016; Wang, Wan, Li et al. 2016); reductions in fuel consumption as a result of improved transport and logistics planning; and use of advanced tracking and monitoring systems (Gabriel and Pessel 2016; Müller, Dotzauer, and Voigt 2017). On the social dimension, I4 T offers abundant opportunities for employees to learn new technologies, thereby improving morale and motivation (Herrmann et al. 2014; Peukert et al. 2015). I4 T offers improved work environment and safe working conditions for employees (Kamble, Gunasekaran, and Gawankar 2018).

2.6. *Lean practices and sustainable performance*

LMP supports cost reduction and improved profits, resulting in increased productivity and competitive advantage (Singh, Singh, and Singh 2018; Todorut et al. 2016). LMP is claimed to be a necessary component in achieving SOP (Mollenkopf et al. 2010; Wong and Wong 2014). It is found that the benefits of LMP, such as improved product quality and reduced inventory levels, are linked to lower pollutant levels (Fliedner 2008; King and Lenox 2001). Value stream mapping, one of the favourite lean tools, is found to contribute to the environmental protection through the mapping of raw materials, energy, and water usage by a process or product (Vinodh, Arvind, and Somanaathan 2011). LMP results in waste minimisation, increased return on investments, and improvement in health and safety-related challenges (Ratnayake and Chaudry 2017). The integration of lean with environmental management systems results in the reduction of implementation costs associated with the environmental improvement programme, marginal costs related to pollution management, dispersion of toxic compounds, and savings in energy and resources (Belhadi, Touriki, and El Fezazi 2018; Zhan et al. 2018). In the social sustainability dimension, the integration of LMP and high-involvement work practices are found to positively affect occupational safety (Camuffo, De Stefano, and Paolino 2017). LMP aimed at improved housekeeping, material handling, kaizen, and workplace safety results in fewer accidents, improving occupational health and safety (Souza and Alves 2018). Sajan et al. (2017) report a positive relationship between LMP and economic, environmental, and social sustainability performance measures.

The above discussions not only motivate us to investigate the direct effects of I4 T on LMP and SOP but also to investigate the mediating effects of LMP on the relationship between I4 T and SOP. Therefore, in this study, we hypothesise that:

H1: I4 T have a significant direct and positive influence on SOP.

H2: I4 T have a significant direct and positive influence on LMP.

H3: LMP has a significant mediating effect on the indirect relationship between I4 T and SOP.

The proposed research model used in this study is presented in Figure 1.

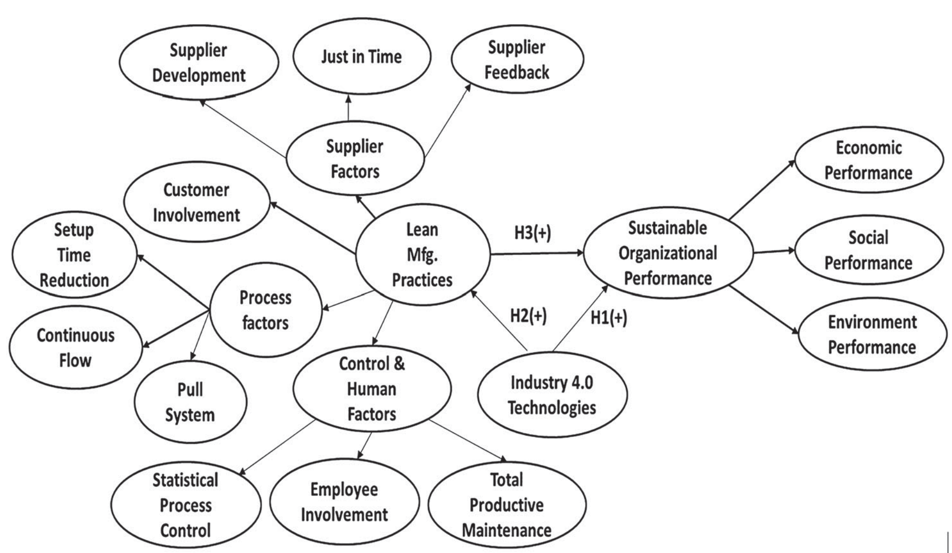

Figure 1. Research model.

3. Research methods

3.1. Instrument development

A questionnaire-based survey methodology was used to investigate the causal relationships between the constructs and obtain generalisable statements on the research questions raised in the present study (Pinsonneault and Kraemer 1993). The measurement scales used to design the survey instrument were derived from previously published literature having favourable psychometric properties. The responses for the measurement items on LMP and SOP were collected using a five-point Likert scale, with the extreme points ranging from strongly disagree (1) to strongly agree (5) (Chen and Paulraj 2004). The measurement items used for LMP were developed using Shah and Ward (2007) and Sanders, Elangeswaran, and Wulfsberg (2016). The measurement items used for SOP measured the effect of implementation of LMP and/or I4 T on the SOP of the manufacturing firms. The items for SOP were developed using Zhu, Geng, and Lai (2011), Sajan et al. (2017), and Kamble, Gunasekaran, and Gawankar (2018). The anchors for the five-point Likert scale used for measuring I4 T ranged from not considering it (1); planning to consider it (2), representing initial stages of discussion with the vendors; considering it currently for implementation (3), which means that the technology has been planned for and on the way to implement; is being implemented (4); to implemented successfully (5). The measurement scale intends to measure the implementation level of I4 T in the study organisations and represent the maturity of the organisation in terms of adequate preparations made by them to implement the technology. The companies are yet to appreciate the complex features of I4 T and therefore are uncertain about what benefits I4 T will offer them in the future (Bibby and Dehe 2018). The adoption of I4 T in Indian manufacturing companies is still in its initial stage and slowly gathering momentum (Kamble, Gunasekaran, and Sharma 2018). Therefore, the measurement items on I4 T were aimed at measuring the degree of I4 T implementation and not the level of successful implementation. The measurement items for I4 T were based on previous studies (Kamble, Gunasekaran, and Gawankar 2018; Tortorella and Fettermann 2018). The questionnaire was developed in the English language, and the survey was conducted in three stages to ensure the measures were valid and reliable. Firstly, based on the guidelines of DeVellis (2012), the instrument was discussed with eight experts drawn from industry and academics for ambiguity, clarity, and appropriateness of measures. The group of experts consisted of two senior academicians from the field of operations management, two senior professors with backgrounds in manufacturing and technology management, two senior industry practitioners from the field of manufacturing, and two industry practitioners from the field of information technology. The subjective validity by the experts ensured that the selected measures addressed the subject of the study (Dillman 1978). Secondly, to ensure good reliability and validity, a pilot study was conducted on 48 postgraduate students pursuing Masters in Industrial Engineering and Management at one of the leading academic institutions in India. Only students who had prior work experience in the manufacturing sector and are aware of the concepts in I4 T and LMP could participate in the survey. The pilot survey was administered personally by one of the co-authors based in India to ensure that the selected students fulfilled the above criteria. The Cronbach alpha (α) values were computed, and the items with low α scores (below 0.70) and that raised concerns about ambiguity, clarity, and appropriateness for the students were modified and reframed. The final measurement items used in the study are listed in Table 4.

3.2. Data collection

The data for the study was collected using a cross-sectional email survey drawn from a list of manufacturing companies from four cities in India (Mumbai, Pune, Bangalore, and Chennai). The scope of the study included automobile, chemical, and pharmaceutical manufacturing companies. Pune has a dedicated auto industry cluster with more than 750 large and medium-sized manufacturers producing auto and automobile components (Pugaokar 2015); Chennai accounts for nearly 35% revenue share in automobile manufacturing and has a share of 60% in the country's automotive export (Menon 2010). Further, Mumbai and Bangalore have recognised manufacturing hubs for pharmaceutical and chemical products (CCI 2012). A link to the online questionnaire was sent to 600 respondents representing 120 companies drawn from the Centre for Monitoring Indian Economy (CMIE) database. The manufacturing companies were randomly selected from the four manufacturing cities in order to obtain a representative sample of the population. Participation in the survey was kept voluntary, with follow-up messages sent at regular intervals by the co-authors based in India. A cover letter accompanied the email, requesting that the respondents fill their responses only if they were aware of the I4 T and LMP concepts and had minimum work experience of one year in manufacturing organisations. The recipients of the online questionnaire were requested to submit their responses within a time frame of four weeks. The final sample size for the study was 205 respondents with a success rate of 34%, representing 115 manufacturing companies (automobile: 48%, chemical: 33%, and pharmaceuticals: 18%). The selected sample varied on the dimensions of number of employees (less than 100 employees: 56%, 100–500 employees: 33%, and above 500 employees: 11%), type of ownership (private: 62%, private listed: 26%, and joint ventures: 12%), and type of products manufactured (finished products: 55%, components: 25%, and raw material: 20%). The

205 practitioners varied on the characteristics of position (plant manager: 11%, manufacturing/operations manager: 26%, supply chain manager: 18%, logistics manager: 22%, procurement/purchasing manager: 23%) and work experience (1–5 years: 10%, 6–10 years: 44%, 11–15 years: 36%, 15 years and above: 10%). All statistical analysis was performed on the collected survey responses after averaging the items with multiple responses to obtain a single value for each item (Huo et al. 2015; Venkatraman and Grant 1986). Therefore, the effective sample size of the study is considered 115 manufacturing organisations. Considering the resource constraints and efforts in collecting data on an exploring topic involving the integration of I4 T and LMP, the sample size of 115 manufacturing organisations was found to be sufficient for conducting confirmatory factor analysis (CFA) and structural equation modelling (SEM) (Sideridis et al. 2014; Wolf et al. 2013). The design of the online survey was such that responses to all the questions were compulsory, without which the respondent was not allowed to make the final submission of the instrument. This compulsion eliminated the issue of missing values and incomplete questionnaires, making all the questionnaires usable for analysis. However, to account for the nonresponse bias of the early and the late submissions, Kolmogorov and Smirnov, two independent sample tests, were performed on the data received from 205 respondents (Ryans 1974). The late respondents to the surveys are roughly similar to non-respondents (Oppenheim 1966). The online survey was conducted during the period 16 April to 25 July 2018. 165 questionnaires were received within the first eight weeks (up to 15 June 2018) from the date of publishing the online questionnaire, with two follow-up reminders. The remaining 40 questionnaires were received at a much slower rate requiring additional reminders (three) to be sent during the remaining period (five weeks).

3.3. Analytical tools and techniques

The Kolmogorov–Smirnov two independent sample test was used to analyse the presence of non-response bias. Harman's single factor score was used to test the presence of common method bias (CMB) (Podsakoff and Organ 1986). Kurtosis and Skewness were computed to ascertain the normality of data (Curran, West, and Finch 1996). Other techniques such as factor loadings, composite scale reliability (CSR), and average variance extracted (AVE) were used to test the convergent and discriminant validity of the measurement items. The guidelines used to test for convergent validity included factor loading values above 0.50 (Hair et al. 2014), composite scale reliability (CSR) values above 0.70 (Gefen, Straub, and Boudreau 2000; Hair et al. 2014), and the average variance extracted (AVE) values above 0.50 (Fornell and Larcker 1981; Hair et al. 2014; Pallant 2000). The hypothesised measurement model was confirmed using the Chi-square value (χ^2), degrees of freedom (df), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), non-normated fit index (NFI), comparative fit index (CFI), and root mean square error of approximation as per the guidelines suggested by Carmines and McIver (1981) and Hair et al. (2014). The direct effects of I4 T on LMP and SOP were analysed using standardised regression coefficients obtained from SEM analysis. Sobel test (Sobel 1982) and vaf score (Shrout and Bolger 2002) were used to analyse the indirect effects of I4 T on SOP with LMP as the mediating variable. All the tests were performed using IBM SPSS 25 and IBM AMOS 25.

4. Results and discussion

4.1. Non-response and common method bias

The collected responses were divided into an early response group and a late response group. The early response group represented 165 respondents (*questionnaires received within the first eight weeks of the survey*), and the late response group included 40 respondents (*questionnaires received during the last five weeks of the survey)*. The mean responses for all the constructs used in the study were tested for differences using a 'Kolmogorov-Smirnov' test (Wallace and Mellor 1988). The results showed no significant differences in the two groups, indicating the absence of non-response bias (Table 3). Further, the total variance of 40% explained by one factor suggested that the data was not affected by CMB.

4.2. Measurement model

The Skewness and Kurtosis presented the maximum absolute values of 1.52 (std. error of 0.23) and 2.83 (std. error of 0.45) respectively, which were within the threshold limits (Skewness < 2, Kurtosis < 7), indicating no significant deviations from the standard values (see Table 4). The factor loading values presented in Table 4 and the CSR and AVE values presented in Table 5 indicated that the measurement items had no convergent validity issues (factor loadings > 0.50, CSR > 0.70, and AVE > 0.50) except for the construct STR (AVE of 0.439), which was dropped from the final SEM analysis. The STR showed lack of discriminant validity and was found to be related to JIT. The issue was discussed with the same group of experts consulted before for establishing the subjective validity. Although the mean values for the STR were high, the experts identified two reasons for the lack of validity. Firstly, the supply chain practitioners might have perceived both STR

Table 3. Non-response bias.

Constructs	Most extreme differences: Absolute	Positive	Negative	Kolmogorov-Smirnov statistic	Asymp. Sig. (2-tailed)
I4T	.166	.166	− .048	.941	.338
SF	.233	.000	− .233	1.320	.061
JIT	.190	.000	− .190	1.079	.195
SD	.128	.044	− .128	.726	.667
CI	.194	.018	− .194	1.100	.177
PS	.095	.065	− .095	.542	.931
CF	.109	.109	− .051	.619	.838
STR	.152	.024	− .152	.860	.451
SPC	.108	.014	− .108	.610	.850
EI	.150	.028	− .150	.851	.464
TPM	.103	.029	− .103	.585	.884
EP	.133	.017	− .133	.752	.623
SP	.134	.000	− .134	.761	.609
EVP	.101	.003	− .101	.572	.899

Grouping variable: 1-Early respondents ($N = 165$ respondents), 2-Late respondents ($N = 40$ respondents).

and JIT as common measures for reducing the manufacturing lead time. Secondly, the selected study organisations (chemical processing, automobile/auto-component manufacturing, and pharmaceutical companies) produced fewer or single product variants, requiring lesser or no setup changes. Therefore, the researchers felt that dropping STR will not have a major impact on the study.

The findings from Table 5 show that the square root AVE of all the constructs (except for STR) is higher than the correlations between the specific construct and all the other constructs in the model, indicating no major discriminant validity concerns (Cooper and Zmud 1990; Hair et al. 2014). The CFA was performed to confirm the hypothesised model structure. The measurement model indicated a satisfactory model fit with 1924 positive degrees of freedom, $\chi^2 = 3463.27$, χ^2/df ratio = 1.80, goodness of fit index (GFI) = 0.87, adjusted goodness of fit index (AGFI) = 0.84, non-normed fit index (NFI) = 0.89, comparative fit index (CFI) = 0.91, and root mean square error of approximation (RMSEA) = 0.08, indicating that the selected constructs show uni-dimensionality.

4.3. Hypothesis testing using SEM model

The full structural model developed for this study to test the integrated effect of I4 T, LMP, and SOP included seventeen latent factors (twelve first-order levels, four-second order levels, and one third-order level) and fifty-nine observed variables (see Figure 2). The observed variables represented the underlying latent constructs. SEM was used to test the hypothesis formulated for the study.

4.4. Direct effects of I4 T on SOP and LMP

SEM analysis was performed to test the direct effects of I4 T on the SOP (H1) and LMP (H2). The hypothesis H1, stating that the I4 T positively influences the SOP, was found to be significant ($\beta = 0.369.$, $p = 0.000$), with a value of R^2 (0.136) for the dependent variable SOP. The hypothesis H2, stating that I4 T positively influences the LMP, was also supported ($\beta = 0.62$, $p = 0.000$), with a significant value of R^2 (0.40) for the dependent variable LMP.

4.5. Mediating effect of LMP on I4 T and SOP

The results of the full structural model with all three constructs, viz., I4 T, LMP, and SOP, as shown in Figure 2, indicated that I4 T have a positive influence on the LMP ($\beta = 0.62$, $p = 0.000$) and a negative and insignificant effect on SOP ($\beta = -0.11$, $p = 0.29$). The overall R^2 values for the dependent variables LMP ($R^2 = 0.40$) and SOP ($R^2 = 0.56$) were found to be significant. Although the full structural model in Figure 2 indicated the presence of LMP as a mediating variable, the same was required to be confirmed by evaluating the direct and indirect effects of the I4 T on SOP. The estimates derived from the results of SEM analysis were used for investigating the mediating effect LMP has on the relationship between I4 T and SOP. Three possible outcomes are associated with a mediation analysis: no mediation, partial mediation, and full

Table 4. Factor loadings and normality parameters.

Construct Details	Factor loadings (λ)	Mean Values	Std. Deviation	Skewness	Kurtosis
Industry 4.0 Technologies (I4 T)					
Our firm is in the process of implementing or implemented cloud computing (CC)	.816	3.08	1.39	– 0.18	– 1.20
Our firm is in the process of implementing or implemented big data analytics (BDA)	.802	3.21	1.38	– 0.28	– 1.23
Our firm is in the process of implementing or implemented Internet of Things (IoT)	.716	3.58	1.42	– 0.59	– 0.98
Our firm is in the process of implementing or implemented additive manufacturing (AM)	.655	3.02	1.48	– 0.11	– 1.42
Our firm is in the process of implementing or implemented robotic systems (RS)	.585	2.90	1.44	0.05	– 1.29
Our firm is in the process of implementing or implemented augmented reality (AR)	.740	3.01	1.52	– 0.12	– 1.50
Supplier Feedback (SF)					
Our company is always in close contact with our key suppliers (SF1)	.840	3.90	1.12	– 1.09	0.67
Our company provides quality and delivery performance feedback to all our key suppliers. (SF2)	.876	3.89	1.18	– 1.14	0.57
Our company puts maximum efforts to develop a long-term relationship with our key suppliers (SF3)	.882	3.90	1.17	– 1.19	0.72
Just in Time (JIT)					
Our company involves all our key suppliers in the NPD process (JIT1)	.793	3.88	1.04	– 0.69	– 0.09
Our key suppliers make JIT delivery to our plant. (JIT2)	.771	3.80	1.07	– 0.64	– 0.13
Our company has a formal supplier certification programme in place (JIT3)	.789	3.92	1.07	– 0.89	0.26
Supplier Development (SD)					
Our suppliers thrive to achieve an annual reduction in costs (SD1)	.532	3.75	1.13	– 0.64	– 0.47
Our principal suppliers are located in the close vicinity of our plants (SD2)	.680	3.52	1.13	– 0.28	– 0.67
Our company has a well-established system to communicate important issues with key suppliers (SD3)	.516	3.83	1.04	– 0.89	0.78
Our organisation make efforts to have a lesser number of suppliers in each category (SD4)	.616	3.76	1.10	– 0.68	– 0.26
Our inventory is managed by suppliers (SD5)	.668	3.50	1.11	– 0.22	– 0.61
Supplier evaluation is done on the total cost purchase and not per unit price (SD6)	.636	3.82	1.01	– 0.96	1.05
Customer Involvement (CI)					
Our firm is in close contact with our customers (CI1)	.551	4.22	0.95	– 1.32	1.74
Our firm collects quality and delivery performance feedback from customers (CI2)	.641	4.31	0.87	– 1.55	2.83
Our firm involves direct involvement of customers in existing product improvement and NPD process (CI3)	.740	3.55	1.17	– 0.35	– 0.72
Our customers take active participation in existing product improvement and NPD process (CI4)	.587	3.77	1.17	– 0.46	– 1.04
Our customers share the present and future demand information with our firm (CI5)	.608	3.90	1.04	– 0.75	0.02
Pull System (PS)					
Our production is pulled by the shipment of finished goods (PS1)	.812	3.60	1.31	– 0.82	– 0.39
Our production at work-stations is pulled by the current demand of the next work-station (PS2)	.819	3.64	1.31	– 0.83	– 0.35
We have adopted a pull production system (PS3)	.793	3.63	1.33	– 0.81	– 0.44
Kanban, squares, or containers of signals are used for production control (PS4)	.595	3.63	1.34	– 0.80	– 0.50
Continuous Flow (CF)					
The products requiring similar processing steps are grouped into related categories (CF1)	.706	3.56	1.21	– 0.30	– 1.09
The products requiring similar routing steps are grouped into related categories (CF2)	.730	3.68	1.12	– 0.48	– 0.45

(*Continued*)

Table 4. Continued.

Construct Details	Factor loadings (λ)	Mean Values	Std. Deviation	Skewness	Kurtosis
The equipment is grouped with an objective to have a continuous flow of families of products (CF3)	.725	3.74	1.08	− 0.40	− 0.75
The factory layout is based on the families of products (CF4)	.648	3.88	0.97	− 0.74	0.39
Setup Time Reduction (STR)					
Our employees adopt various setup time reduction techniques (STR1)	.560	3.64	1.10	− 0.57	− 0.17
Our firm continuously work towards reducing the setup time (STR2)	.570	3.52	1.17	− 0.72	− 0.25
Our firm has low set up times of equipment (STR3)	.797	3.95	1.07	− 0.95	0.38
Statistical Process Control (SPC)					
We cover majority of the equipment/processes under SPC (SPC1)	.521	3.62	1.16	− 0.76	− 0.07
We use statistical techniques to control the process variance (SPC2)	.582	3.73	1.14	− 0.60	− 0.30
We display defect rate charts on the shop floor (SPC3)	.611	3.79	1.10	− 0.81	0.01
We use cause effect diagrams to identify quality issues (SPC4)	.564	3.71	1.30	− 0.88	− 0.27
Process capability studies are pre-requisites to any new product launch (SPC4)	.553	3.90	1.10	− 1.14	0.92
Employee Involvement (EI)					
We believe that our shop floor employees play a significant role in problem-solving teams (EI1)	.528	4.10	0.99	− 1.28	1.44
The suggestion scheme programme at our firm is driven by our employees (EI2)	.730	4.07	0.94	− 1.23	1.95
The product/process improvement efforts are led by our shop floor employees (EI3)	.713	3.99	1.01	− 1.06	0.96
We provide cross-functional training for our shop floor employees (EI4)	.666	3.77	1.09	− 0.70	− 0.07
Total Productive Maintenance (TPM)					
A significant portion of our time is committed for planned equipment maintenance related activities every day (TPM1)	.777	4.14	0.94	− 1.36	2.30
Our firm carries regular maintenance of all equipment (TPM2)	.759	4.00	0.98	− 0.96	0.99
Our firm maintains complete and updated maintenance records for all the equipment (TPM3)	.740	4.05	0.97	− 1.10	1.37
The equipment maintenance records are shared with all the shop floor employees for active participation (TPM4)	.774	4.16	0.90	− 1.26	2.12
Sustainable Organization Performance (SOP)					
Economic Sustainability (EP)					
Reduced costs of production (EP1)	.910	3.97	1.09	− 1.11	0.86
Improved profits (EP2)	.904	3.95	1.07	− 1.13	1.03
Reduced product development costs (EP3)	.903	3.96	1.08	− 1.11	0.90
Decreased energy costs (EP4)	.887	3.90	1.04	− 0.94	0.68
Reduces inventory costs (EP5)	.920	3.94	1.03	− 1.06	1.01
Reduced rejection and rework costs (EP6)	.906	3.91	1.06	− 1.10	1.02
Decreased raw material purchasing costs (EP7)	.917	3.90	1.05	− 1.10	1.05
Decreased waste treatment costs (EP8)	.892	3.85	1.09	− 0.85	0.32
Social sustainability (SP)					
Improved working conditions (SP1)	.801	4.23	0.87	− 1.27	2.07
Improved workplace safety (SP2)	.738	4.13	0.91	− 0.97	0.89
Improved employee health (SP3)	.777	4.15	0.92	− 0.99	0.86
Improved labour relations (SP4)	.811	4.11	0.91	− 0.95	0.92
Improved morale (SP5)	.776	4.23	0.85	− 1.07	1.13
Decreased work pressure (SP6)	.765	4.16	0.85	− 0.91	0.77
Environmental Sustainability (EVP)					
Reduction of solid waste (EVP1)	.718	4.04	1.11	− 1.26	1.02
Reduction of liquid waste (EVP2)	.747	4.03	1.09	− 1.09	0.53
Reduced gas emissions (EVP3)	.697	3.87	1.14	− 0.96	0.32
Reduced energy waste (EVP4)	.772	3.88	1.14	− 0.91	0.15
The decrease of consumption of hazardous/harmful/toxic materials (EVP5)	.668	3.96	1.05	− 1.05	0.82
Improvement in firm’s environmental situation (EVP6)	.754	3.94	1.04	− 1.08	0.98

Table 5. Convergent and discriminant validity results.

	CSR	AVE	EI	SF	JIT	SD	CI	PS	CF	STR	TPM	EP	SP	EVP	I4T	SPC
EI	0.86	0.67	**0.82**													
SF	0.98	0.94	0.44	**0.97**												
JIT	0.96	0.88	0.57	0.55	**0.94**											
SD	0.87	0.59	0.60	0.45	0.60	**0.77**										
CI	0.83	0.52	0.50	0.51	0.59	0.56	**0.72**									
PS	0.99	0.97	0.55	0.41	0.61	0.55	0.47	**0.99**								
CF	0.83	0.55	0.60	0.40	0.56	0.64	0.68	0.59	**0.74**							
STR	0.66	0.44	0.58	0.57	0.98	0.61	0.61	0.62	0.56	**0.66**						
TPM	0.96	0.87	0.63	0.49	0.59	0.59	0.51	0.56	0.60	0.59	**0.93**					
EP	0.99	0.93	0.49	0.22	0.37	0.45	0.33	0.41	0.33	0.38	0.47	**0.97**				
SP	0.97	0.83	0.55	0.39	0.47	0.49	0.38	0.47	0.38	0.49	0.59	0.63	**0.91**			
EVP	0.95	0.75	0.55	0.31	0.53	0.41	0.46	0.57	0.35	0.54	0.53	0.59	0.69	**0.87**		
I4T	0.87	0.54	0.42	0.21	0.34	0.37	0.38	0.55	0.51	0.38	0.32	0.32	0.22	0.37	**0.74**	
SPC	0.88	0.58	0.73	0.47	0.68	0.72	0.67	0.76	0.74	0.70	0.71	0.57	0.57	0.65	0.68	**0.76**

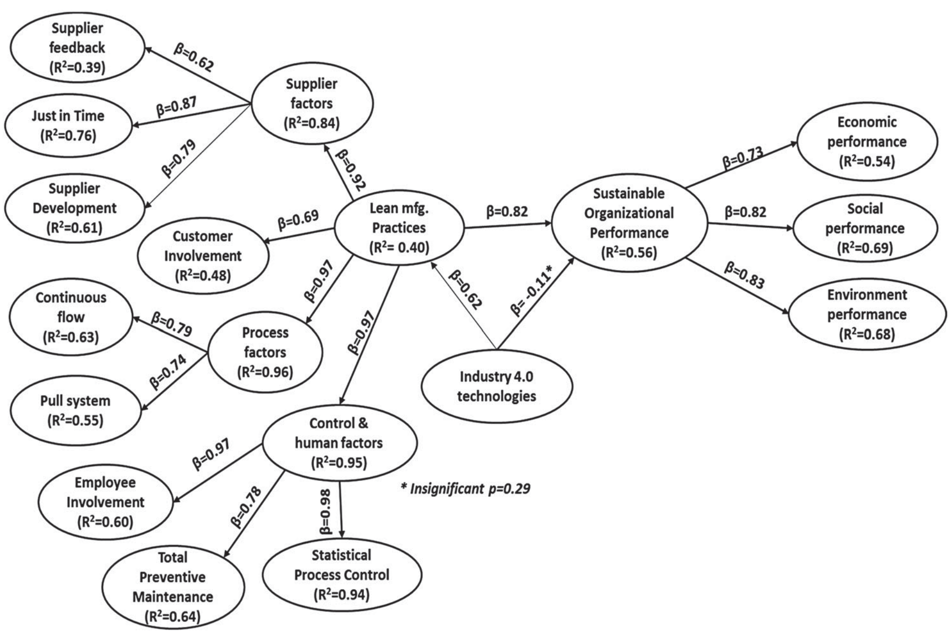

Figure 2. Full structural model.

mediation. Partial mediation exists when the direct and indirect effects (from I4 T to SOP) via the LMP are significant. Full mediation exists when the direct effect (from I4 T to SOP) in the presence of LMP is insignificant, and the indirect effect of I4 T on SOP is significant. No mediation exists when the indirect effects are insignificant and also when the direct effects between the I4 T to LMP and LMP to SOP are insignificant. The model was tested for mediation effects in AMOS, using bootstrapping to report the significance of both direct and indirect effects. The results of the standardised regression coefficients presented in Table 6 supported the hypothesis (H3) stating that LMP has a significant mediating effect on the indirect relationship between I4 T and SOP. The results in Table 7 based on the Sobel test show that the mediated path I4T → LMP → SOP is significant with $\beta = 0.508$ at $p < 0.001$. The ratio of indirect effects of the mediated path to the total effects was calculated using a variance accounted for (vaf) score. The vaf score of 1.15 (vaf > 1) indicates that the LMP explains 100% of the variance in the mediated path, representing a full mediation. LMP loaded strongly on the process factors ($\beta = 0.97$), supplier factors ($\beta = 0.92$), and control & human factors ($\beta = 0.97$), followed by the customer factors ($\beta = 0.69$). The SOP loaded strongly on environmental performance dimension ($\beta = 0.83$), followed by social performance ($\beta = 0.82$) and economic performance ($\beta = 0.73$). The statistically validated model exhibits a high explanatory power, with I4 T and LMP explaining 56% of the total variance in SOP ($R^2 = 0.56$).

The summary of the hypothesis is presented in Table 8.

Table 6. Standardized regression coefficients.

Hypothesis	Direct beta without mediation	Direct beta with mediation	Indirect beta	Mediation type observed
Mediation I4T-LP-SOP	0.369*	− .110	0.00	Full

*Indicates significance at $p < 0.001$.

Table 7. Significance of I4T → LMP → SOP path.

Indirect path	Mediated path	Path coefficient	Z statistic
I4T → SOP	I4T → LMP → SOP	0.508	3.765*

*Indicates significance at $p < 0.001$.

Table 8. Hypothesis test results.

Hypothesis	Hypothesis statement	Estimate	S.E.	C.R.	Sig.	Result
Direct effects						
H1*	I4T → SOP	0.369	0.081	3.296	***	Supported
H2*	I4T → LMP	0.620	0.119	5.427	***	Supported
Mediating effect						
H3**	I4T → LMP → SOP	0.508	–	–	–	Full mediation exists

*Only the direct effects analysed using structural equation modelling.
**Both the direct and indirect effects were analysed using bootstrapping-structural equation modelling.
***Indicates significance at $p < 0.001$.

The objectives of this study included investigating the direct effects of I4 T on SOP and LMP, and the mediating effect of LMP on the relationship between I4 T and SOP. The present study identified the presence of a positive and significant direct relationship between the I4 T and the SOP ($\beta = 0.369$, $R^2 = 0.136$). The previous studies had claimed the existence of a positive relationship between the I4 T and SOP (Beifert, Gerlitz, and Prause 2018; de Sousa Jabbour et al. 2018; Kamble, Gunasekaran, and Gawankar 2018; Quezada et al. 2017). However, we provide an empirical validation to this relationship in this study. We also empirically validate the relationship between the I4 T and LMP ($\beta = 0.620$, $R^2 = 0.40$), supporting the findings of Tortorella and Fettermann (2018) and the theorised claims made in the previous studies (Buer, Strandhagen, and Chan 2018; Kolberg and Zühlke 2015; Sanders, Elangeswaran, and Wulfsberg 2016). The mediated path I4T → LMP → SOP was found to be significant, with I4 T and LMP explaining 56% of the variance in the SOP.

5. Conclusions

The current study focused on investigating the direct effects of I4 T on LMP and SOP, and the mediating effect of LMP on the relationship between I4 T and SOP. This is one of the preliminary studies that provide empirical validation of the relationship between I4 T, LMP, and SOP. The findings reveal that I4 T have a positive and direct influence on LMP and SOP. The study also identified LMP as a significant mediating variable. The theoretical and managerial implications of the study are discussed below.

5.1. Theoretical implications

The topic of industry 4.0 is gaining increased attention in the field of research, which is evident from the high number of calls for research papers from reputed journals such as the *International Journal of Production Economics*, the *International Journal of Production Research*, *Production Planning and Control*, *Resources, Recycling and Conservation*, the *Journal of Manufacturing Technology Management*, and *Computers and Industrial Engineering*. Theoretically, the study advances the literature in three ways. Firstly, this is one of the first studies that empirically investigates the relationship between I4 T, LMP, and SOP. The previous literature indicated the influence of either the I4 T or LMP on SOP.

Nevertheless, none of the studies had empirically investigated the combined effects of I4 T and LMP on SOP. Secondly, the study investigated the claim that intermediate variables provide meaningful insights into the relationship between information technology-driven resources and organisational performance (Banker et al. 2006; Heim and Peng 2010; Tippins and Sohi 2003). In our study, LMP was found to be a significant mediating variable providing more profound insights into the relationship between I4 T and SOP, thus contributing to the literature on information technology. Thirdly, the study presents a list of validated measurement items for I4 T, LMP, and SOP from the perspectives of manufacturing companies in India. These scales have been statistically tested for convergent and discriminant validity and may be adapted for similar studies in other industrial sectors with minor modifications.

5.2. Managerial implications

The findings of the study present critical implications for the industry practitioners and consultants involved in the implementation of I4 T and LMP in manufacturing organisations. The findings indicated that the I4 T are in various stages of implementation in the Indian manufacturing organisations. IoT, BDA, and CC were found to be given higher consideration for implementation followed by AM, AR, and RS. Organizational challenges such as financial constraints, poor management support, low awareness, reluctant behaviour, and lack of competency are the significant implementation barriers of I4 T (Luthra and Mangla 2018). The practitioners should design strategies to overcome these barriers to improve I4 T implementation in manufacturing companies. The practitioners should aim at achieving a high level of process integration by deploying appropriate I4 T as an outcome of the efficient cyber-physical system and human-machine interface (Kamble, Gunasekaran, and Gawankar 2018). The companies should clearly outline their sustainable objectives and prioritise the different I4 T based on the contributions they can make in creating smart products and processes (Schmidt et al. 2015). The practitioners should also take into consideration the various aspects of human performance and organisational culture in implementing and managing I4 T for improved SOP (de Sousa Jabbour et al. 2018). The findings indicate the statistical significance of almost all the LMP dimensions, which implies that Indian manufacturing organisations acknowledge the contribution of LMP in achieving SOP. One of the LMP dimensions, STR (setup time reduction), was required to be dropped from the study due to the issue of discriminant validity. STR exhibited higher correlation with the other construct JIT (Just in time). The significant direct effects between the I4 T and LMP indicated positive influence of I4 T on LMP, which implies that manufacturing organisations should commit to implement I4 T to make the factory smart and lean. The results suggest that implementation of the future oriented technologies of I4 T makes a factory smart thereby, supporting the organisations to overcome the barriers of lean implementation (Sanders, Elangeswaran, and Wulfsberg 2016). The effectiveness of the supplier factors that include supplier feedback, JIT, and supplier development systems may be improved through the increased use of BDA, sensors, CC, and other IoT devices (Schmidt et al. 2015). This improved integration will enhance the sustainable outcomes of the organisation by ensuring on-time product delivery, supply network optimisation, and logistics reliability (Bose and Pal 2005; Caballero-Gil et al. 2013). It is implied that the I4 T implementation in the manufacturing organisations will transform the lean manufacturing system into a lean virtual manufacturing network that will connect all the manufacturers and suppliers in a single network, enabling the sharing of tangible (machines, equipment, human, etc.) and intangible assets (data, knowledge, and information) between the connected parties (Sanders, Elangeswaran, and Wulfsberg 2016). It is further implied that I4 T can contribute to the customer involvement factors by improving the present level of customisation offered, based on analysing the customer-generated data using BDA (Shrouf, Ordieres, and Miragliotta 2014). AM also promises to offer increased customisation, reduce manufacturing waste, and decrease the manufacturing lead time (Kamble, Gunasekaran, and Gawankar 2018).

Although the findings indicate that I4 T has a direct and positive effect on SOP, this effect is magnified in the presence of LMP as a mediating variable. This implies that I4 T may not contribute to the SOP if implemented as a standalone application in the absence of LMP. LMP is focused on developing human integration, which is crucial for overcoming the I4 T implementation barriers, and therefore may act as an essential facilitator for achieving SOP (Wong and Wong 2014). LMP treats people as valuable assets and encourages a high level of participation in the organisation, which is essential for any change management programme (Bubshait and Farooq 1999; Wilkinson, Marchington, and Dale 1993). Therefore, it is implied that the successful implementation of LMP enables the organisations to be prepared for initiating the implementation process for I4 T.

Given the above findings, practitioners should not exclude the presence of other mediating variables, such as circular economy practices or green supply chain practices, that may influence the effects of I4 T on SOP.

5.3. Limitations

Some basic features of I4 T and assumptions made in this study lead to a few limitations. The assumptions made in the study are listed below.

5.3.1. The familiarity of the respondents with the I4 T

I4 T is a relatively new technology, and most of the manufacturing companies in India are in the process of achieving full-fledged deployment. Therefore, the views expressed by the respondents may not be purely based on their practical experience with the technology. Longitudinal studies are recommended to be conducted to understand how the successful deployment of I4 T will influence the findings of the present study in the future.

5.3.2. Integration of I4 T

In this study, I4 T is presented as a collection of different technologies, such as BDA, CC, IoT, additive manufacturing, etc. However, all these technologies serve different purposes, and a company may decide to implement only selected technologies. This aspect is not considered in the present study. Further, the scope for integration within these technologies is also not examined in the present study. Therefore, it is suggested that future studies should consider the type of I4 T as the moderating variable to study the effect of LMP on SOP.

5.3.3. One standard solution for all manufacturing value chains

In the present study, the sample respondents were drawn from the chemical, pharmaceutical, and automobile industry. However, as mentioned above, the IT and strategic choices for different manufacturing chains vary, and therefore future studies may be carried on specific industries to create a more generalised understanding of the relationship between I4 T, LMP, and SOP. The characteristics of the manufacturing organisations may be used as moderating factors.

5.3.4. The objective measurement model for sustainable performance evaluation

The SEM analysis focuses on analysing the cause–effect relationships between the identified constructs of I4 T, LMP, and the SOP. However, these relationships fail to act as a good managerial decision support for the practitioners, and only provide the information on the causal relationships between the constructs. It is therefore suggested that future studies should focus on developing a good decision support system that may be used for predicting the SOP. The future studies may be developed using Bayesian network to express the causal dependencies between the constructs using conditional probabilities (Gupta and Kim 2008). This will provide a more objective assessment of the model and help for better prediction and diagnosis of the already developed model.

Disclosure statement

No potential conflict of interest was reported by the authors.

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