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Impact of Process Product and Social Performance on Digitalization of Indian SMEs

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Abstract

This study explores key factors such as process product and social as independent variables to examine the level of adoption of digital technology as a dependent variable in Indian automotive small and medium enterprises (SMEs). Partial least squares structural equation modeling (PLS-SEM) data were collected from 40 small and medium enterprises in automotive sector. The analysis tested the six hypotheses and found that five were statistically significant indicating that factors related to process (H1b and H1a), product (H2b and H3a), and social (H2a) are positively associated with industry digitalization. Notably, 78.9% of the variance in the dependent variable is explained by the independent variable for small enterprises whereas 85.9% of the variance in the dependent variable is explained by the independent variable for medium enterprises. These findings highlight the need to achieve or strengthen the remaining factors or practices regarding social performance (H3b) for effective adoption of industry digitalization effectively in small and medium enterprises in India. This research contributes to a deeper understanding of these practices and offers practical as well as theoretical implications for enhancing these practices especially in small and medium enterprises in India.

Keywords
Lean Automation; digitalization; process; product; social

1. Introduction
Manufacturing businesses must constantly innovate to remain competitive in the face of several obstacles. Process innovation, or the introduction of new procedures or methods of operation, is a form of innovation. Process innovation is a significant source of innovation, particularly in small and medium-sized businesses (SMEs), (Yu & Schweisfurth, 2020). The world is currently experiencing a new industrial revolution that is developing more quickly than its predecessors. It is distinguished by the merging or integration of virtual and physical worlds through components that allow for a higher level of process automation and digitization (Silva et al., 2020). Regardless of their place of origin, industrial businesses worldwide now seek to gain a competitive edge by implementing digitalization and automation (DA) concepts (A. Schumacher & Sihn, 2020). Given that SMEs are headed toward Industry 4.0, it is critical to provide them with direction on how to get there. However, it is crucial that some of the pillars of change are integrated throughout the organization prior to any kind of transformation. Therefore, SMEs must be able to determine whether

they are prepared to undergo this digital transformation (Genest & Gamache, 2020). I4.0 emphasizes end-to-end digitalization and industrial ecosystem integration, although some of these technologies were already in place during the third industrial revolution (Agostinho & Baldo, 2020). Production systems are significantly affected by digital transitions. The use of intelligent and networked manufacturing technologies in factories is continuously increasing (S. Schumacher et al., 2021). By investing in cutting-edge technology methods, such as automation and robotics, the European industry is transforming and envisioning a more digitalized, sustainable manufacturing sector that will boost the region's competitiveness to dominate the global market by 2030(Johansen et al., 2021). The increased process automation and digitization brought forth by the Fourth Industrial Revolution, or "Industry 4.0," is transforming the manufacturing sector. The aim of Industry 4.0 (Woschank & Dallasega, 2021) is to integrate IT with production and logical processes. I4.0 is a new industrial paradigm, according to researchers, that can help businesses perform better financially, environmentally, and socially (Stock et al., 2018). Businesses can achieve Lean Automation (LA), which, according to (Kolberg et al., 2017), seeks more changeability and quicker information flows to satisfy future market demands, by combining LM with I4.0. Thus, it is evident that these two interventions offer skills that, when combined, can push businesses to achieve significantly higher performance standards. I4.0 enables increased levels of mass customized processes, goods, and services, as well as new product and service advancements and business model changes, all of which enable businesses to attain higher performance levels (G. L. Tortorella, Narayanamurthy, et al., 2021). Changes to an organization's intangible (such as behaviors and organizational culture) and tangible (such as management practices and technologies) elements may be included in a successful LA deployment (G. L. Tortorella, Saurin, et al., 2021a). Therefore, by extending the research on the impact of LA practices regarding process, product and social on the industry digitalization individually, we answer the following question:

RQ: How do these practices impact on digitalization of Indian SMEs?

The remainder of this article is arranged as follows: In Section 2, we look at the pertinent literature and the evolution of the hypothesis. Section 3 presents the research technique, which includes developing a questionnaire, gathering data, and analyzing it. In Section 4, we discuss the structural equation modeling (SEM). Section 5 presents a discussion and implications for practice and research and Section 6 illustrates the limitations and possible future research directions.

2. Literature review

2.1 Lean Production

It is a method of continuous improvement that can find and cut waste or non-value-added activities by letting the product flow at the customer's request. The Toyota Production System (TPS), which manufactures goods in accordance with customer specifications with the least amount of waste, serves as the foundation for the development of a lean mindset (Ali et al., 2020). Lean techniques such as Kaizen, value stream diagrams, 5s, and comprehensive quality control have recently been shown to improve corporate success recently (Naeem et al., 2021). According to (Mamede et al., 2023), it is reasonable to apply lean concepts to the deployment of human-robot collaboration (HRC) and to use lean technology to improve HRC, according to (Mamede et al., 2023). Because Lean Production (LP) is known to have positive effects on financial and operational performance through a systematic and continuous search for waste reduction and improvements, some researchers argue that an integrated application of LP and I4.0 technologies could ease current management challenges and push manufacturers to even higher performance standards (G. L. Tortorella, Rossini, et al., 2021). Nevertheless, prior research has widely employed the method of gauging the maturity of LP implementation by evaluating the degree of acceptance of pre-established processes (G. L. Tortorella & Fettermann, 2018). Although research on the relationship between operational performance and the operationalization of lean manufacturing processes tends to differ, it is generally agreed that lean manufacturing adoption is favourably correlated with improved operational performance (Buer et al., 2021). However, waste minimization impacts more SMEs than large organizations, while JIT is more important for large corporations than small and medium-sized businesses (SMEs)(Belekoukias et al., 2014). Successful lean implementation depends on LP techniques and principles being properly aligned, as is necessary in any socio-technical system (Gambatese et al., 2017).

2.2 Lean Automation

The operationalization of Lean Production (LP) techniques using digital automation technologies is known as Lean Automation (LA). Although the idea of LA was first developed in the 1990s, technological advancements at that time restricted its use (Kolberg & Zühlke, 2015). One method of attaining an organization's overall enhanced performance is through the use of new, cutting-edge technologies under the auspices of I4.0. Strong links between goods, procedures, and services are made possible by I4.0 through CPS and IoT (Saraswat et al., 2024). In terms of manufacturing process automation, the car industry which is perhaps the most automated industrial sector, is approximately 20 to 30 years ahead of the wood product industry (Landscheidt et al., 2017). More significantly, CPS are regarded as one of the primary facilitators of lean automation because they can provide the requisite level of adaptability and integration between business systems and production processes (Lee et al., 2019). Devices that provide manufacturing process detection, measurement, monitoring, and control can be integrated to enable industrial automation (Ionel & Opran, 2022). The well-known connection between I4.0 and LP has also revived ideas like "Lean Automation" that existed prior to I4.0's recognition. To satisfy future market expectations, LA implementation allows for great changeability and shorter information flows (Kolberg et al., 2017). Indeed, a number of authors contend that manufacturers may be able to overcome current obstacles and attain previously unheard-of Total Quality Management & Business Excellence with the right integration of I4.0 and LP, here referred to as LA (G. L. Tortorella, Rossini, et al., 2021). However, while some studies examine more thorough LA implementation, they often only cover a limited number of techniques and technologies used in a particular industrial setting, which makes it difficult to draw generalizable conclusions about the topic (G. Tortorella et al., 2021). Hence, to examine the relationship between these practices and industry digitalization, we formulate the following hypothesis:

H1a: Industry digitalization of **small businesses** in the automotive sector is positively impacted by the adoption of processes that are *process* oriented.

H1b: Industry digitalization of **medium businesses** in the automotive sector is positively impacted by the adoption of processes that are *process* oriented.

LMP and sustainability performance metrics related to the economy, environment, and society are positively correlated, (Kamble et al., 2020). A few studies have offered recommendations for improving the organization of LA implementation. A total of 260 examples in Germany were used by (Dombrowski et al., 2017) to determine the connections between I4.0 and LP, demonstrating synergistic pair wise correlations. To increase productivity and wellbeing, STS theory focuses on cooperative optimization and a shared emphasis on the development of social and technological components (Eijnatten & Goffau, 1994). LA presents values and develops capabilities that can be controlled jointly by integrating ideas from LP and I4.0 to help organizations perform better (G. L. Tortorella, Narayanamurthy, et al., 2021). Additionally, studies examining the simultaneous use of LP and I4.0 showed that business performance improved. The few studies that have been conducted specifically show how LA adoption impacts performance improvements (G. L. Tortorella et al., 2018). The following hypotheses were developed to investigate this relationship:

H2a: Industry digitalization of **small businesses** in the automotive sector is positively impacted by the adoption of product-oriented practices which is *product* oriented.

H2b: Industry digitalization of **medium businesses** in the automotive sector is positively impacted by the adoption of product-oriented practices which is *product* oriented.

While LA techniques may comprise the technical (tangible) components necessary for successful implementation, LA principles may highlight social (intangible) aspects. To appropriately modify people's mindsets prior to the actual adoption of LA practices, it is ideal for LA concepts to be generally accepted within an organization (G. L. Tortorella, Saurin, et al., 2021b). The conflicts and consequences of lean automation have also been emphasized in several studies (Robinson et al., 2012). According to (Vlachos et al., 2023), a survey of manufacturers in Brazil and India that had adopted Industry 4.0 technology and lean methods revealed that more sophisticated technologies had less of an impact on operational performance than more straightforward ones. Based on contextual factors such as the socioeconomic setting (Rossini et al., 2022), we examined the variations for businesses in LA adoption, which is meant to be the application of both I4.0 and LP. According to (G. L. Tortorella et al., 2023), there may be operational, financial, and human resource changes may occur in the logistics sector. A total of 147 manufacturers participated in this cross-sector survey. To examine this relationship, following hypotheses were formulated:

H3a: Industry digitalization of **small businesses** in the automotive sector is positively impacted by the adoption of practices which is *social* oriented practices.

H3b: Industry digitalization of **medium businesses** in the automotive sector is positively impacted by the adoption of practices which is *social* oriented practices.

3. Methodology
3.1 Questionnaire development
To ensure that the respondents could answer the final questionnaire honestly and as best as they could, they were requested to refer to their own corporate position. Forty practitioners from manufacturing organizations that had adopted lean automation in the previous three years were polled. They were asked to respond to a questionnaire: Q1, which detailed the company context and respondent's characteristics, Q2, was divided in to four parts or constructs namely *process oriented, product oriented, factory digitalization and social oriented* using automation tools such as IoT, CPS, AI and other digital technology used. A five-point Likert scale was used to respond to all questions. The data are collected from small and medium manufacturing firms in India covering the automotive sector. Forty Indian manufacturers implementing lean implementation with automated methods constitute the final sample size. We performed multivariate data techniques using PLS SEM or smart PLS 4.0 to analyze the collected data.

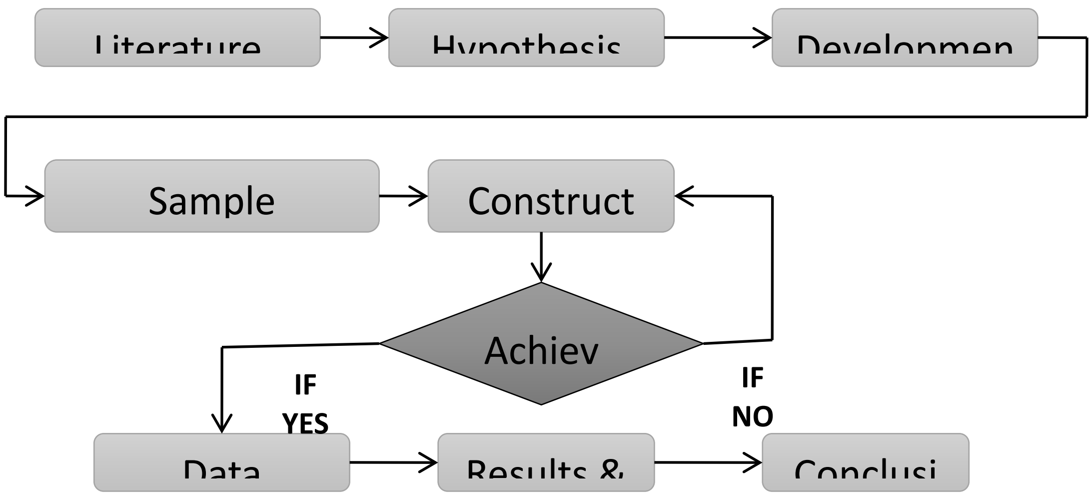

Figure 1. Methodology

3.2 Measure
Aligned with our research question, the questionnaire consisted of two parts. The first part collected information on respondents characteristics (e.g. respondent role, professional experience) and organization (company size and sector, annual turnover, investment in plant and machinery) to identify the demographic profile of the sample. Second, respondent had to indicate the level of automation or industry digitalization over the past three years using automation tools. For that, we applied a five-point Likert scale which varies from 1(strongly disagree), 2(disagree), 3(neutral), 4(agree), 5(strongly agree).

3.3 Sample selection and data collection
In April and May 2024, 120 small and medium-sized manufacturing businesses in India that were either online or offline and implementing lean automation on a small or large scale were given the questionnaire. Online questionnaires were distributed using Google Forms, emails, and other applications. Thirty of those were received, yielding a response rate of 25%. Six of the 30 responses were disqualified due to inadequate questionnaire completion. Following up with the industry person by email, the Watts app, and direct phone calls in July and August 2024 resulted in 21 responses being added to our database; five of these responses were removed due to lack of information. Thus, 40 respondents constitute the final sample, yielding a response rate 34%. For medium-sized sectors, as indicated in Table 4, 55% of the sample comes from businesses with more than 500 employees, while 45% come from businesses with fewer than 500 employees. In terms of positions within their organizations, 30% were analysts/engineers, 45% were managers or directors, and 25% were supervisors/coordinators. Thirty percent had less than five years of experience, while 70 percent had more than five years. Because of the need to examine the differences between them, the automobile industry accounts for 85% of production, with the remaining 15% coming from other industries such as food and leather. We determine the size of the industry with the aid of the Government of India's (GoI) criteria for

small and medium-sized businesses regarding annual sales and investment in plant and machinery. In terms of the respondents' professional experience, 35% had less than ten years of experience, and 65% had more than ten years.

Similarly, 35% of the sample for small-scale industries comes from businesses with more than 500 employees, whereas 65% comes from businesses with fewer than 500 employees. In terms of positions within their organizations, 35% were analysts/engineers, 25% were managers or directors, and 40% were supervisors/coordinators. Six percent had less than five years of experience, while 14 percent had more than five years. In terms of manufacturing, the automotive industry accounts for 95% of all manufacturers, with the remaining 5% coming from other industries such as leather. This is due to the fact that it is necessary to examine the differences between these industries. Sixty percent of the respondents had more 10 years of professional experience, while 40 percent had less than ten years as shown in **Table 1**

Table1. Sample Characteristics (n=40)

Medium Scale Industries(n=20) Respondents with Lean automation			**Small Scale Industries(n=20) Respondents with Lean automation**		
Company size			**Company size**		
<500	11	55%	<500	7	35%
>500	9	45%	>500	13	65%
Respondent Role			**Respondent Role**		
Supervisor/Coordinator	5	25%	Supervisor/Coordinator	8	40%
Manager/Director	9	45%	Manager/Director	5	25%
Analyst/Engineer	6	30%	Analyst/Engineer	7	35%
Respondent Experience			**Respondent Experience**		
< 5 years	14	70%	< 5 years	14	70%
> 5 Years	6	30%	> 5 Years	6	30%
Industry Sector			**Industry Sector**		
Automobile	17	85%	Automobile	19	95%
Other(Leather, food)	3	15%	Other(Leather, food)	1	5%
Annual Turnover			**Annual Turnover**		
>250 cr	20	100%	>50 cr	20	100%
Investment in plant/machinery			**Investment in plant/machinery**		
>50 cr	20	100%	>10 cr	20	100%
Respondent Professional Experience			**Respondent Professional Experience**		
< 10 years	13	65%	< 10 years	12	60%
> 10 years	7	35%	> 10 years	8	40%

3.4 Construct validity and reliability

Partial least squares structural equation modelling, (PLS-SEM), is an analysis technique for identifying or developing predictive models. Exploratory research, is better than the general linear structural relationship model, especially when it comes to causal model analysis between latent variables (Pavlou & Fygenson, 2006). Unlike covariance-based structural equation modelling (CB-SEM), which is evaluated by the covariance matrix, PLS-SEM is suitable for small sample analysis (Ringle et al., 2012). To investigate the association between the research variables, this study employed PLS-SEM. To determine path coefficients and significance, the PLS Algorithm was primarily used to carry out recurrent sampling 5000 times (Henseler & Chin, 2010).

4. Result Analysis using SEM-PLS

4.1 Confirmatory Factor Analysis

Table 2. Confirmatory Factor Analysis (CFA) Results for MSI and SSI

MSI and SSI		MSI				SSI			
Construct	Indicators	Factor Loading	CA	CR	AVE	Factor Loading	CA	CR	AVE
Process	P1:-Using digital automation without sensors	0.834	0.886	0.913	0.699	0.727	0.817	0.917	0.548
	P2:-Using digital automation with process control sensors	0.848				0.763			
	P3:-Using systematic remote production monitoring and control using MES and SCADA or PLC	0.698				0.649			
	P4:-Using digital automation with sensors for identifying products and operating conditions.	0.661				0.778			
	P5:-Adoption level of lean automation is good	0.783				0.776			
Product	PR1:-Collection, processing and analysis of data using automation tools.	0.781	0.825	0.881	0.591	0.909	0.851	0.94	0.592
	PR2:-Using digital services like IOT,ICT or product service system in to the products	0.904				0.908			
	PR3:-Reduce process variance using digital sensors	0.810				0.826			
	PR4:-Lower setup time in our plant by practicing automation technology.	0.651				0.671			
	PR5:- Through digital automation, customers are actively involved in both present and future product offers.	0.672				0.422			
Factory digitalization	FD1:-Robotic stations on production line.	0.903	0.925	0.945	0.782	-0.11	0.822	0.835	0.659
	FD2:-Highly automated machines	0.678				0.665			
	FD3:-RFID tags at the products	0.858				0.807			
	FD4:-Using digital tools to communicate with customers.	0.967				0.928			
	FD5:-Use of smart manufacturing technologies within your company	0.977				0.826			
Social	S1:-Positive impact of lean automation practices on employees behavior	0.600	0.771	0.809	0.524	0.762	0.758	0.768	0.511
	S2:-Positive impact of lean automation practices on customer relationship management	0.634				0.631			
	S3:-Agree or disagree with respect to the use internal lean automation practices.	0.834				0.834			
	S4:-Virtual meetings using Zoom and Microsoft Teams for effective communication	0.645				0.72			
	S5:-Positive impact of automation practices on human resource management	0.845				0.599			

Discriminant and convergent validity were assessed using SEM-PLS. Discriminant validity in PLS-SEM was assessed using Fornell and Larcker Creation and Heterotrait-Monotrait (HTMT) ratio. Similarly, PLS-SEM uses Average Variance Extracted (AVE),Composite Reliability (CR), Cronbach's alpha (CA), and outer loadings to verify convergent validity (Pereira et al., 2024). We also checked all of the constructs' relationships, and they were all significant and positive. Table 2, displays the results of Confirmatory Factor Analysis (CFA) for medium-sized industries (MSI) and small-scale industries (SSI). CFA evaluates each construct's internal consistency, reliability, and convergent validity using statistical measures such as Cronbach's alpha (CA), Composite Reliability (CR), Average

Variance Extracted (AVE), and individual item loadings. These results reinforce the systematic validation of the research variables, and increase the validity and reliability of this study.

The factor loading value for '*process*' construct in medium-sized industries (MSI) falls between 0.637 to 0.957. For this specific construct, the composite reliability (CR) was 0.913, which is above the threshold limit of 0.7, suggesting robust internal consistency, and Cronbach's alpha (CA) was 0.886, indicating a solid level of internal consistency. Furthermore, there is good convergent validity because the average variance extracted (AVE) is 0.699, which is higher than the threshold value of 0.5. The factor loading value for the process construct in small-scale industries (SSI) falls between 0.649 and 0.778. For this specific construct, the composite reliability (CR) was 0.917, which is above the threshold limit of 0.7, suggesting robust internal consistency, and Cronbach's alpha (CA) was 0.817, indicating a solid level of internal consistency. Good convergent validity was also indicated by the average variance extracted (AVE), which is 0.548, above the threshold value of 0.5.

For '*product*' construct, factor loading for MSI ranges from 0.655 to 0.906 showing good correlation or dependability among construct and its measuring items with Cronbach's alpha (CA) 0.825 and CR 0.881 follows AVE 0.591. In the case of SSI, the factor loading ranged from 0.424 to 0.908, CA of 0.851, CR of 0.94 and AVE of 0.592 which is above the threshold value. For the construct '*factory digitalization'* factor loading for MSI ranges from 0.637 to 0.975 showing good correlation or dependability among the construct and its measuring items with Cronbach's alpha (CA) 0.925 and CR 0.945 follows AVE 0.782. For SSI, factor loading ranges from -0.11 to 0.928, CA was 0.822; CR was 0.835, and AVE was 0.659 which was above the threshold value. Likewise, factor loading for the construct *'social'* varies from 0.605 to 0.848, CA is 0.771, CR is 0.809, followed by AVE 0.524 in the case of MSI whereas, for SSI the factor loading was 0.602 to 0.834, CA was 0.748, CR is 0.768 and AVE is 0.511. All values are above the threshold showing good correlation, internal consistency, and convergent validity.

Table 3. Descriptive statistics (MSI & SSI) for data normality

	MSI				SSI			
Factors	**Mean**	**STD**	**Kurtosis**	**Skewness**	**Mean**	**STD**	**Kurtosis**	**Skewness**
P1	3.4	1.647	-1.471	-0.433	3.2	0.919	0.334	-1.546
P2	3.6	1.838	-1.348	-0.870	4.6	0.516	-2.277	-0.484
P3	2.8	0.919	0.396	-0.601	3.8	0.632	0.179	0.132
P4	3.2	1.687	-1.572	-0.389	2.9	1.370	-1.466	-0.751
P5	3.3	1.337	-0.852	-0.334	4.1	0.738	-0.734	-0.166
PR1	2.8	1.317	-0.751	0.088	2.7	1.160	-1.227	-0.342
PR2	3.4	1.506	-0.671	-0.615	3.1	1.449	-0.987	-0.214
PR3	3.2	1.398	-0.420	-0.439	3.1	0.876	0.613	-1.465
PR4	3.2	1.135	0.552	-0.478	3.3	1.160	0.512	-0.727
PR5	2.8	1.549	-1.276	0.188	3.1	1.197	-0.369	-0.233
FD2	2.7	1.252	-0.066	0.280	2.3	0.823	-1.043	-0.687
FD3	3.4	1.578	-1.159	-0.620	3.4	1.578	-1.159	-0.620
FD4	3.4	1.776	-1.577	-0.612	2.8	1.317	-1.449	-0.643
FD5	3.4	1.506	-1.487	-0.127	2.6	0.843	0.370	-0.389
S1	3.4	1.265	-0.026	-0.544	4.1	0.876	-1.734	-0.223
S2	4.1	0.994	0.914	-1.085	3.8	0.789	-1.074	0.407
S3	3.2	1.619	-1.695	-0.204	3.9	0.876	-1.734	0.223
S4	3.9	1.287	1.864	-1.338	4.2	0.789	-1.074	-0.407
S5	3.2	1.476	-1.065	-0.425	3.7	0.949	-0.347	-0.234

Skewness ranges from -1 to +1

Kurtosis ranges from -3 to +3 for 5 pt rating scale

Mean should not be more than 5 for five pt rating scale

4.2 Descriptive statistics for data normality

The survey data may have a common method bias because all independent and dependent variables were extracted from a single instrument (questionnaire) in a single phase. Experts and English language professionals created a carefully constructed survey answer form that eliminated the CMB issue and guaranteed that no questions were double-barred or confusing. Since it is impossible to completely exclude CMB from the survey responses, we analyzed CMB-related issues quantitatively. For evidence of data normality descriptive statistics were performed. All skewness and kurtosis values for MSI and SSI were below the threshold as shown in **table 3 above** (Bokhorst et al., 2022).

4.3 Structural Equation Modeling (SEM)

The hypothesized model shown in **Fig.2** represents the construct and its indicators. The constructs are represented by blue circles and indicators are represented by rectangles. We aim to investigate how the external construct affects the endogenous construct. Thus we pay particular attention to industry digitalization also called factory digitalization out of the total construct. Industry digitalization is an endogenous construct in our situation, whereas the remaining constructs are exogenous (independent).

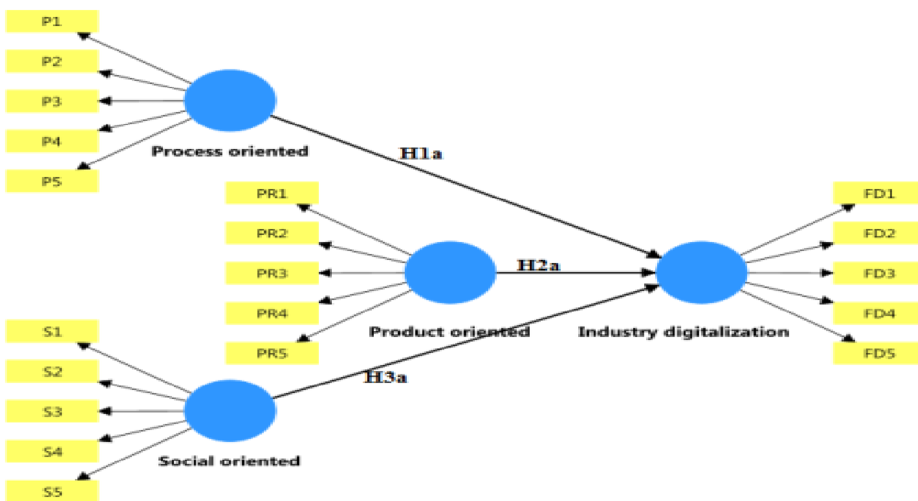

Figure 2. Hypothesized model (SSI) with indicators, construct and hypothesis from Smart PLS 4.0 (Before Run)

Figure 3, represents the structural model with the construct and its indicators, outer loading and path coefficients between latent construct. In this case indicators of the exogenous constructs such as *process, social* and *product* constructs are more than 0.5 indicating a strong relationship. Additionally, the value of the path coefficient between the *process* construct and the *industry or factory digitalization* construct is 0.084 indicating a weak positive relationship between the two constructs. The path coefficient between the *social* and *industry digitalization* constructs is 0.423 indicating a moderate positive relationship. Likewise, the path coefficient value between the *product* and *industry digitalization* construct is 0.618 which indicates a strong positive relationship between these two. The measure of goodness of fit (R^2) is 0.789 which means that 78.9% of the variance in the dependent variable (endogenous) is explained by the independent variable (exogenous) and 21% is unexplained. In the case of industry *digitalization construct* one indicator FD1 was removed because of poor correlation (Pereira et al., 2024).

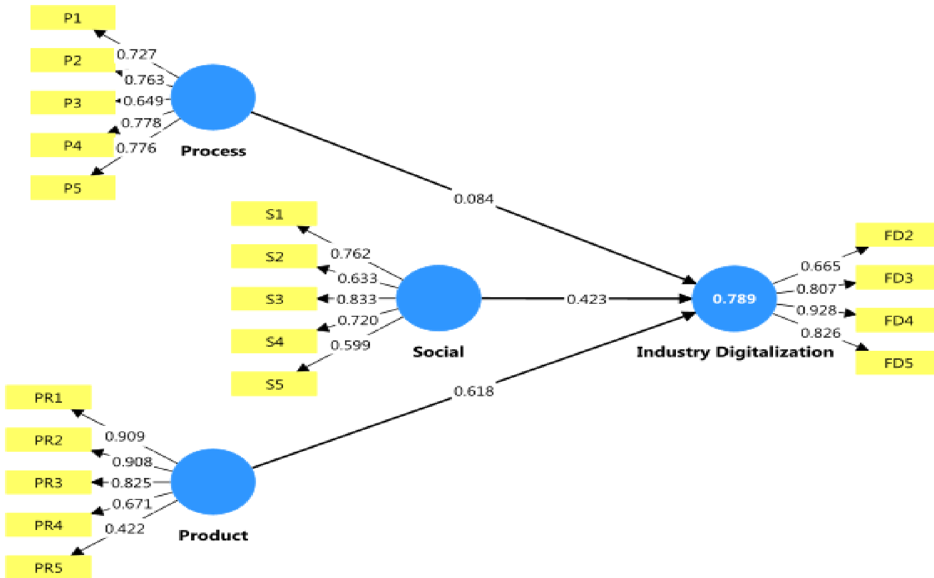

Figure 3 SEM model for Small Scale Industry (After Run)

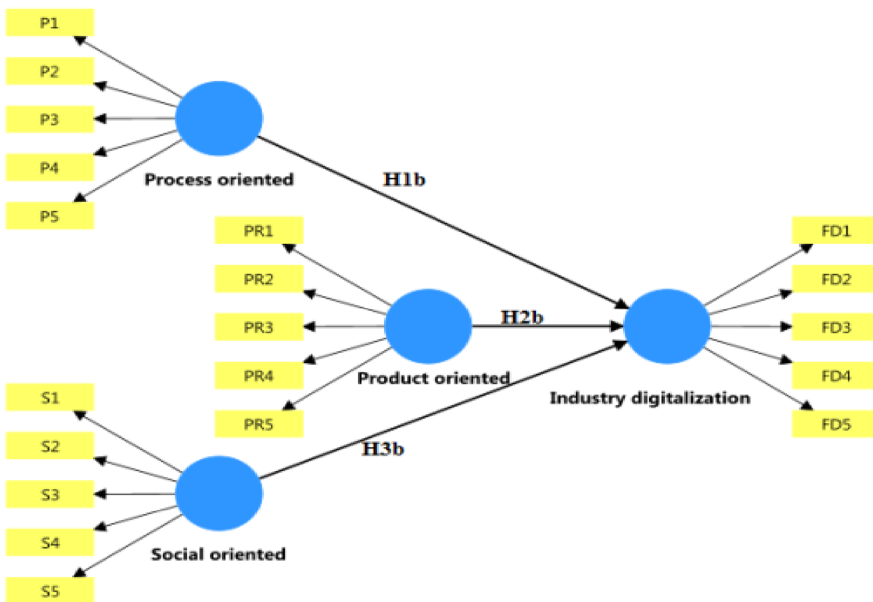

Figure 4. Hypothesized model for MSI (Before Run)

The hypothesized model for MSI (before run) of smart PLS 4.0 as shown in **Fig. 4** represents the construct and its indicators for medium scale industry.

Figure 5 represents the structural model with the construct and its indicators, outer loading and path coefficients between latent constructs. The indicators of the exogenous constructs such as *process, social* and *product* constructs are more than 0.5 indicating a strong relationship. Additionally, the value of the path coefficient between the *process* construct and the *industry or factory digitalization* construct is 0.892 indicating a good relationship between the two constructs. The path coefficient between the *social* and *industry digitalization* constructs is -0.110, indicating a weak negative relationship. Likewise, the path coefficient value between the *product* and *industry digitalization* constructs is 0.159 which indicates a weak positive relationship between these two. The measure of goodness of fit (R^2) is 0.859, which means that 85.9% of the variance in the dependent variable (endogenous) is explained by the independent variable (exogenous) and 14% is unexplained.

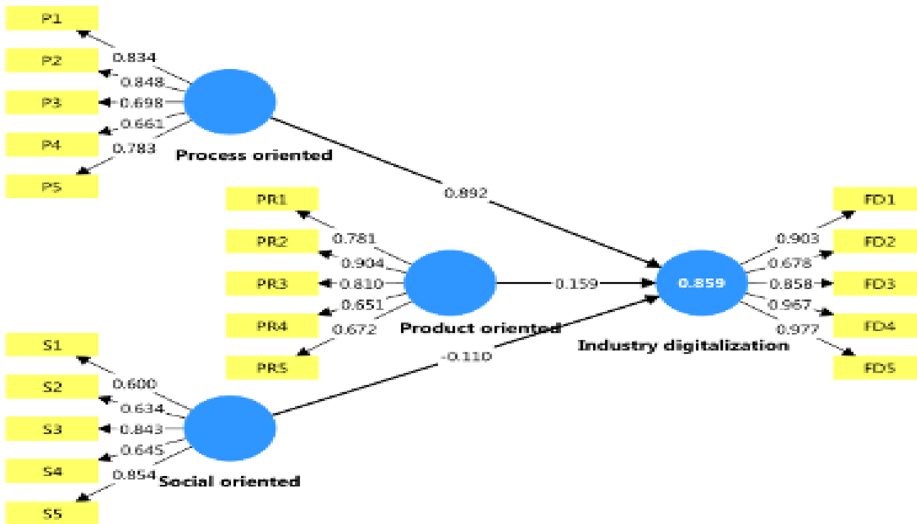

Figure 5. SEM model for MSI (After Run)

The Heterotrait-Monotrait (HTMT) values for MSI and SSI are shown in **Table 4**. HTMT had a threshold value of 0.9. The study's discriminant validity was guaranteed using HTMT analysis [45]. Notably, for MSI the highest HTMT ratio for *social* and *product* construct was observed as 0.912 exceeding the threshold value, indicating some similarity. In SSI, the highest HTMT ratio was 0.816 for *social* and *factory digitalization* constructs. Strong statistical support was provided by the HTMT analysis, confirming that each construct in our study has unique properties. The results of the heterotrait-monotrait ratio test for MSI and SSI are shown below. Compared with the Fornell and Larcker criterion, the HTMT ratio is now thought to be a more reliable test for discriminant validity (Pereira et al., 2024).

Table 4 Heterotrait-Monotrait ratio

Heterotrait-monotrait ratio (HTMT)		
Construct	**MSI**	**SSI**
Process oriented <-> Factory digitalization	0.802	0.801
Product oriented <-> Factory digitalization	0.87	0.791
Product oriented <-> Process oriented	0.845	0.647
Social oriented <-> Factory digitalization	0.772	0.816
Social oriented <-> Process oriented	0.662	0.537
Social oriented <-> Product oriented	0.912	0.602

Table 5 presents the Fornell and Larcker matrix which provides a thorough examination of the values for all the constructs. As we can see the *factory digitalization* construct has the highest value (0.884), corresponding to its row and column representing the correlation with other constructs such as *process, product* and *social* construct. This is the square root of the AVE of each construct. Similarly, for *process*, *product* and *social.* We also go through cross-loadings, some of the items were problematic and the possible explanation is the low AVE (Pereira et al., 2024).

Table 5. Fornell and Larker's Matrix

MSI	Factory digitalization	Process oriented	Product oriented	Social oriented
Factory digitalization	0.884			
Process oriented	0.794	0.836		
Product oriented	0.739	0.727	0.769	
Social oriented	0.722	0.708	0.676	0.724
SSI	**Factory digitalization**	**Process**	**Product**	**Social**
Factory digitalization	0.727			
Process	0.637	0.742		
Product	0.674	0.629	0.77	
Social	0.606	0.344	0.249	0.715

5. Discussion

5.1 Main Findings

Table 6. represents the decision about the hypothesis, considering that path coefficients (β) are essential when assessing the casual relationships between constructs. Generally, path coefficients above 0.20 are significant, whereas those below 0.10 are not regarded as statistically significant. For MSI, the path coefficients (β) for all three constructs were calculated using the PLS-SEM algorithm. The β coefficient for *process* and *digitalization* construct is 0.892, indicating a strong positive relationship, similarly, for *social* and *digitalization*, the β coefficient is -0.110, indicating a weak negative relationship. Similarly, the β coefficient for *product* and *digitalization* construct is 0.159, indicating a moderate relationship. Whereas the β coefficient for SSI, *process* and *digitalization* construct is 0.084, indicating a weak positive relation, for *social* and *digitalization* construct, it is 0.423, indicating a strong positive relationship and in the case of *product* and *digitalization* construct, it is 0.618, indicating strong positive relationship (Pereira et al., 2024). To measure the effect size of the exogenous variable (process, social and product) on the endogenous variable, (digitalization) f-square (f^2) was calculated using the PLS-SEM algorithm for MSI and SSI. The effect size of *process* construct on the *digitalization* construct was 0.988, indicating a large effect. Likewise, the effect size *social* on *digitalization* construct is 0.873, indicating a large effect size. Similarly, the effect size of *product* on *digitalization* construct was 0.04 indicating a small effect. Similarly, for SSI, the effect size of *process* construct on the *digitalization* construct was 0.038, indicating a small effect. Likewise, the effect size of *social* on *digitalization* construct is 0.723, indicating large effect sizes. Similarly, the effect size of *product* on *digitalization* construct is 0.911 indicating very large effect (Pereira et al., 2024)(Grace Tetteh et al., 2024).

To check the multi-colinearity of the construct, the variance inflation factor (VIF) was calculated using the PLS-SEM algorithm for MSI and SSI, as shown in table 6 below, indicating no serious multi-collinearity because all the values are below the threshold that is 3.3(Pereira et al., 2024). It is important to note that in MSI, at the 5% level of significance, the t-value of two constructs (process and product) for the two-tailed test is greater than 1.96 that is $t_{critical}$ indicates the statistical significance, whereas one construct is below 1.96, indicating statistical significance. Similarly, in the case of SSI, the t-values of all three constructs for the two-tailed test were greater than 1.96 i.e. $t_{critical}$ indicating statistical significance. We also go through the p-value of all constructs and found that the values of all the constructs lie below the threshold, that is i.e $p_{cal} < p_{critical}$(Grace Tetteh et al., 2024). To assess the variance explained in the dependent (endogenous) construct caused by the entire independent (exogenous) construct, the coefficient of determination (R^2) is calculated. In MSI, the value of R^2 for the endogenous construct is 0.996 followed by an adjusted R^2 of 0.995 (by adjusting all the errors) which means that approximately 90% of the variance in the dependent variable is explained by the independent variable, and 10% is unexplained. Similarly, for SSI, the value of R^2 for the endogenous construct was 0.789 and the corresponding adjusted R^2 . The model fit indices for MSI and SSI are shown in Table 6. The estimated standardized root mean square residual (SRMR) value was 0.056, which was less than the threshold value of 0.08. The model was moderately fitted, as indicated by a normal fit index (NFI) value of 0.724. Likewise, the geodesic discrepancy (d_G) and underweight least square discrepancy (d_ULS) were 2.409 and 1.887, respectively. Similarly for SSI, the SRMR was 0.026 and NFI was 0.669 (Grace Tetteh et al., 2024).

Table 6. R-square, adjusted R-square, F-square and VIF statistics for MSI and SSI

Hypothesis	Path coefficients	f square	VIF	T_{cal}	Cramér-von Mises p value	Hypothesis Testing
Medium Scale Industries(MSI)						
Process -> Digitalization(H1b)	0.892	0.988	2.387	2.191	0.000	**Supported**
Social -> Digitalization(H3b)	-0.110	0.873	2.667	-0.261	0.602	**Not Supported**
Product -> Digitalization(H2b)	0.159	0.04	1.598	1.987	0.000	**Supported**
Small Scale Industries(SSI)						
Process -> Digitalization(H1a)	0.084	0.038	1.736	1.217	0.035	**Supported**
Social -> Digitalization(H3a)	0.423	0.723	1.137	2.063	0.014	**Supported**
Product -> Digitalization(H2a)	0.618	0.911	1.656	2.191	0.010	**Supported**

MSI	**R -Square**	**R-Square adjusted**
Digitalization	0.996	0.995
SSI	**R -Square**	**R-Square adjusted**
Digitalization	0.789	0.736

Statistical significance is confirmed by $T_{cal} > T_{critical}$ (1.96), $p<0.05$

F-square threshold value= 0 to 1

R-square threshold value=0 to 1

VIF<3.3

SRMR(MSI): 0.056 <0.08; NFI(MSI): 0.724; Chi-square: 283.621; d-ULS, d-G, closer to 1

SRMR(SSI): 0.026 <0.08; NFI(SSI): 0.669 ; Chi-square: 263.541 ;d-ULS, d-G, closer to 1

This study tests the effect of an exogenous (independent) construct on an endogenous (dependent) construct. The exogenous constructs were *process, social* and *product* the endogenous construct was *digitalization*. The implementation of practices regarding *process* construct demonstrates a significant direct positive influence on the *digitalization* of small and medium enterprises as indicated by the data (β coefficient 0.084and 0.892, F^2 is 0.038 and 0.988, VIF 1.736 and 2.387, t-value 1.217 and 2.191, $p<0.05$) which satisfies H1 (a, b). Such a relevant influence suggests that companies that use LA should try to ensure that their employees fully understand their needs for the changes being made as well as the fundamental principles and values that the company is pursuing [45]. Regarding H3a, the evidence strongly indicates that *social* construct has a direct positive influence on *digitalization* of small enterprises named as SSI indicated by data (β coefficient 0.423, F^2 is 0.723, VIF 1.137, t-value 2.063 and $p<0.05$). For H3b, the evidence strongly indicates that *social* construct has a negative influence on the *digitalization* of medium enterprises named as MSI indicated by data (β coefficient -0.110, F^2 is 0.837, VIF 2.667, t-value -0.261 and $p<0.05$) showing the partial confirmation of H3**.**It can be suggested that the medium -scale industry needs to be focused on social related issues such as employees behavior, customer relationship management and human resource management which ultimately leads to an increase in the overall digitalization of industry. Regarding H2 (a, b) the evidence strongly indicates that *product* construct has a positive influence on the industry *digitalization* of small and medium enterprises as indicated by the data (β coefficient 0.618 and 0.159, F^2 0.911 and 0.04, VIF 1.656 and 1.598, t-value 2.191and 1.987; $p<0.05$).

5.2 Research Implications

5.2.1 Theoretical Implications

The findings of this study provide theoretical insights in to *process, product and social* performance contributions to *digitalization* of SMEs. This research clarifies that practices related to *process performance* play a crucial role in enhancing the ability of SMEs to reconfigure internal processes quickly in response to market changes, improving agility and innovation. Similarly, the study shows that the practices related to *product performance* play a vital role in the acceleration of industry digitalization by adding automation tools for collection, processing, and analysis of data, using digital services such as IOT, ICT, or product service systems in to the products. Similarly, regarding *social performance*, this study suggests that socially responsible SMEs are more likely to implement ethical artificial intelligence and fair data policies, proactively considering the social consequences of technology adoption.

5.2.2 Practical Implications

The findings of the study provide practical insights for managers or other industry experts by using tools such as ERP systems and accounting software to reduce manual workload, errors and operational costs. The use of lean with agile workflows supported by digital project management tools causes a faster adoption of customer needs or supply chain disruptions. The Integration of IoT with a digital interface causes product performance to be tracked.

6. Conclusion and future scope

This research addresses factors such as *process*, *social* and *product* as independent factors and *digitalization* as dependent factors of SME, to analyze the impact of these practices in the context of industry digitalization. Data has collected from forty small and medium enterprises of automotive sector of India using questionnaire. Further we applied PLS-SEM or Smart PLS 4 for data analysis. The study revealed that *process* performance practices demonstrate a significant direct influence on the digitalization of small and medium enterprises. *Product* performance also demonstrates a significant direct influence on the digitalization of small and medium enterprises. On the hand, practices regarding *social* performance are not satisfactory, indicating a negative influence at the medium scale, whereas it is satisfactory, indicating a positive influence in the small-scale industry. Regarding the limitations and future scope, one of the limitations of this research is its sole focus on the automotive industry, which limits its applicability to other industries and may be the subject of future research. Another constraint is the small sample size; a large sample size can provide more robust results. Moreover, the study is part of a cross-sectional survey, so researchers can use the longitudinal survey method to obtain more robust results.

Ethical statement

This research was carried out in accordance with the highest ethical standards. Participants provided informed consent, and their confidentiality was rigorously maintained. Any conflicts of interest were transparently disclosed and appropriately addressed. The data is accurate, and we have upheld integrity throughout the research process. Any potential biases or limitations have been clearly acknowledged.

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