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Industry 4.0 Indicators and Sustainability Factors to Improve the Efficiency of Indian Process Industries: An Empirical Study

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Abstract: This study examines the relationship between Industry 4.0 indicators and the sustainable production performance of Indian process industries using the PLS-SEM approach in SmartPLS. The study identifies five independent exogenous latent variables, including Smart Manufacturing Systems (SMS), Digital Twin Technology (DTT), Artificial Intelligence and Machine Learning (AIML), Advanced Robotics and Automation (ARA), and Sustainable Supply Chain Management (SSCM). SMS refers to a 'production system' characterized by the use and integration of advanced manufacturing technologies, such as digital technologies, automation, and data analytics, to improve production processes. DTT uses digital representations of physical elements, structures, or procedures to improve performance and anticipate challenges, while AIML focuses on artificial intelligence and machine learning for algorithmic decision-making, predictive maintenance, and process improvement. ARA integrates state-of-the-art robotics and automation to increase production capacity, precision, and versatility. SSCM encompasses the bulk of contributions to integrating sustainability into supply chain management, with objectives such as resource efficiency, waste minimization, and green supply chain management.

The structural latent dependent variable, Production Efficiency, Performance and Sustainability (PEPS), is defined as a measure of the efficiency, performance, and sustainability of production processes, based on ecological and resource-exploitation factors, as well as the quality of services provided. Empirical data were collected via 240 surveys of experts, managers, engineers, and other stakeholders involved in the Indian process industry sector. Several positive

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correlations were observed between the coherently defined Industry 4.0 indicators and improved production efficiency and sustainability. The results indicate that the appropriate engagement with these sophisticated technologies and methodologies has the potential to enhance sustainable production and performance, which is useful for individuals and policymakers.

Keywords: **Industry 4.0, process industry, PLS-SEM, production efficiency, performance and sustainability.**

1. Introduction

The advent of Industrial Revolution 4.0 has redefined the functioning of the manufacturing industry, providing immense opportunities and hurdles in equal measure for process industries worldwide. A new age featuring the interplay among digital, physical, and biological components, Industry 4.0 comprises technologies such as CPS (Cyber-Physical Systems), IoT (Internet of Things), Big Data, and AI (Artificial Intelligence). In the context of Indian process industries, the use of these technologies is vital for improving productivity, operational efficiency, sustainability, and overall performance (Kagermann et al., 2013; Schwab, 2016). Furthermore, the Indian manufacturing industry, which is one of the best for the Indian economy, faces a lot of hindrances due to the prevalent use of 'Industry 4.0' technologies. These constraints include factors such as complexity of technology, lack of financial resources and absence of skills (Kamble et al., 2018; Raj et al., 2020). Information technology integration could bring advantages such as improved production processes, better supply chain management, and greater competitiveness, which justify the effort to tackle these issues (Wang et al., 2016; Sahu et al., 2021). Other factors such as Smart Manufacturing Systems (SMS), Digital Twin Technology (DTT), Artificial Intelligence and Machine Learning (AIML), Advanced Robotics and Automation (ARA), and Sustainable Supply Chain Management (SSCM) are also the major indicators in the Industry 4.0 scenario for improving the sustainability in production systems.

Smart manufacturing systems are the core of Industry 4.0, which integrates automation, digital technologies, and data analytics to enable productive, adaptable factory settings (Frank et al., 2019). An SMS provides a system that allows real-time tracking and steering of production activities, thereby minimizing technical downtime and increasing output. Another important component, termed digital twin technology, entails simulating physical objects and processes in the digital sphere to improve maintenance and performance, as explained (Ghadge et al., 2020; Rejeb et al., 2021). Artificial intelligence and machine learning is a game changer in more robust decision making, performing predictive analysis as well as improving the execution of the production process. Traditionally, AIML is desirable in manufacturing industries because it leads to substantial improvements in product quality, efficiency, and innovative potential (Sahu et al., 2021). Further still, the manufacturing degree is improved with 'more advanced robotics and automation' where accuracy, flexibility, and minimization of human error are required for high-quality products (Hermann et al., 2016). Sustainable supply chain management involves integrating sustainability into supply chain processes. This involves the efficient use of resources, waste minimization, and the application of green strategies that are critical to meeting sustainability objectives in the long run (Bonilla et al., 2018; Mathivathanan et al., 2021). SSCM seeks to help not only improve the environmental performance of manufacturing operations but also enhance the economic and social pillars of sustainability.

According to this study, the latent dependent variables for Production, Efficiency, and Sustainability (PES) broadly capture the effects of adopting Industry 4.0 technologies in production activities. It captures gains in operational efficiency, performance, and sustainability, introducing a holistic assessment of the impacts of advanced manufacturing technologies (Bai et al., 2020; Sanders et al., 2016). This research applies the PLS-SEM model in SmartPLS to examine Industry 4.0 indicators and their impact on production efficiency and sustainability in Indian process industries. Data were collected from 240 stakeholders, including experts, managers, and engineers, through field studies in the industries. There is a need for more studies that provide practitioners with lessons on how to strategically implement technologies in what has come to be known as Industry 4.0 in Indian process industries and to improve sustainable production (Kamble et al., 2019; Min et al., 2019). Embracing Industry 4.0 technologies is transformative for the Indian process industries, fostering creativity, green practices, and cost-effectiveness. By and large, this study highlights the need to do away with the barriers to using advanced technologies and the enhancement of sustainable production and performance.

While Industry 4.0 technologies are widely acknowledged as drivers of industrial efficiency, their role in advancing sustainability within India's process industries remains under-researched. Existing studies predominantly focus on discrete manufacturing sectors in developed economies, neglecting the unique challenges of India's process industries, including regulatory complexity, resource intensity, and socio-economic disparities. This study bridges this gap by empirically analyzing how Industry 4.0 indicators collectively enhance production efficiency and sustainability, offering a roadmap for sustainable industrialization in emerging economies. The present study addresses a critical gap in the literature by examining the synergistic impact of Industry 4.0 indicators-Smart Manufacturing Systems, Digital Twin Technology, Artificial Intelligence and Machine Learning, Advanced Robotics and Automation, and Sustainable Supply Chain Management-on production efficiency and sustainability in Indian process industries. While prior research has explored Industry 4.0 adoption in developed economies, empirical evidence remains limited for emerging economies such as India, where challenges including technological complexity, financial constraints, and skill gaps hinder implementation (Kamble et al., 2018). This study uniquely contextualizes these challenges, emphasizing that integrating sustainability with advanced technologies can address resource inefficiencies, reduce waste, and address operational bottlenecks in sectors such as chemicals, pharmaceuticals, and food processing.

The current study also aims to evaluate the effects of Industry 4.0 indicators on sustainable production and the performance of India's process industries. In particular, it seeks to investigate the relations of five major independent latent variables -smart manufacturing systems, digital twin technology, artificial intelligence and machine learning, advanced robotics and automation, and sustainable supply chain management, with a dependent latent variable – Production Efficiency and Sustainability (PES). The statement of the problem of this study is how the PLS-SEM method, using SmartPLS software, can generate valuable information for decision-making and implementation to increase the efficiency and sustainability of organizations by deploying Industry 4.0 technologies. By employing PLS-SEM, the research quantifies the interdependencies between these indicators and sustainability outcomes, offering actionable insights for policymakers and practitioners striving to balance technological adoption with ecological and economic goals.

2. Literature Review

Industry 4.0 has emerged as truly transformational, promising forthcoming improvements in production amid technological innovations. However, as the current study points out, the Indian manufacturing sector is grappling with the readiness for Industry 4.0 due to various hurdles, including technological, organizational, and regulatory issues (Kamble et al., 2018). It is important to study these barriers to effectively implement the said technologies and harness their fruits. Intelligent or smart technologies, such as artificial intelligence (AI) and augmented reality (AR), are core components of Industry 4.0, as they improve manufacturing processes (Sahu et al., 2021). The prospects of AR have led to the seamless integration of manufacturing systems across the physical and virtual worlds.

To meet modern manufacturing systems' requirements for high precision and a high level of customization, a combination of physical and virtual realities is necessary. The strategic initiative of Industries 4.0, as defined by Kagermann et al. (2013), gives evidence and frameworks to future implementation of the technologies in these industries. Their suggestions are clear and highlight the need for an appropriate environment, including physical structures, educated manpower, and regulations conducive to enhancing creativity and competition in the industry. However, the adoption of these technologies faces certain barriers, such as high costs of deployment of the technology and reengineering of the work structures to incorporate.

According to the various researchers, BDA's (Big Data Analytics) applications are also widespread in the areas of logistics and supply chain management that is reinforced by Industry 4.0. Wang et al. (2016) have drawn attention to a similar potential of BDA, which can change decisions, monitor activities, and ultimately improve the supply chain for overall efficiency. This integration strategy has created more agile and robust supply chains, which are crucial for enhancing competitive edge in today's market. Raj et al. (2020), on the other hand, provide a borderline review of impediments to the uptake of fourth industrial revolution technologies across different nations. Their study highlights the importance of global characteristics in the successful management of the economy. As a result, it was expected that economic, legal, and cultural factors would play a vital role in the application and proliferation of these technologies.

Tornatzky et al. (1990) proposed that the technology innovation process comprises various stages, progressing through linear awareness, completion, and marketing. Learning this process is important for managing the shift to Industry 4.0, as it helps determine key enablers and barriers to innovation. Organizations, thus, have to engage themselves in this strategy slowly, as they seek safety in innovation while experimenting with the new technologies. Frank et al. (2019) analyze the adoption of Industry 4.0 technologies in the manufacturing sector. They indicate that there are so many strategies that companies are not making a total change. The selection of the implementation approach depends on the company's size, industry sector, and readiness level. Implementation should meet all social and technological requirements. Ghadge et al. (2020) points out that the impact of Industry 4.0 is significant in the supply chains. Supply chains have improved and become more transparent due to the adoption of modern technologies such as the Internet of Things, Artificial Intelligence, and Robotics. At the same time, however, such advances pose certain challenges, such as threats to cybersecurity and the need for constant workforce training. Lastly, organizations must consider these issues to maximize the benefits of the fourth industrial revolution. Adoption of such technology remains a challenge due to many barriers that must be addressed at all levels of the organization.

Blockchain is a concept that offers a high level of transparency and is a significant aspect of Industry 4.0. In contrast, Rejeb et al. (2021) conducted a systematic review of the literature on the challenges and opportunities of augmented reality smart glasses for logistics and supply chain management. The relevance of these results is that AR smart glasses can be a game-changer in optimizing throughput and precision of logistics processes. Nonetheless, they may face obstacles such as high prices, technology issues, and user acceptance. The literature provides evidence supporting the assertion that technologies associated with Industry 4.0 hold great promise for transforming manufacturing and supply chain processes. It is important to note that companies must understand and address these barriers to achieve better production outcomes and overall performance under the umbrella of Industry 4.0. Contini and Peruzzini (2022) examined the impact of sustainability on Industry 4.0 through the Triple Bottom Line framework. KPIs' role was investigated to assess the sustainability achieved through Industry 4.0 implementations in the manufacturing industries, especially in the process industries. In another research paper, Contini et al. (2023) investigated the impact of sustainability while implementing the Industry 4.0 technologies for the ceramic sector. Further, the most critical KPIs are also discussed to make the Industry 4.0 rule more realistic and assessable across all sectors. Proper applications of Industry 4.0 technologies make the Indian industries more advanced in production (Gadekar et al., 2022; Patidar et al., 2023; Marinagi et al., 2023), especially in supply chain mechanisms. Further, the authors study the KPIs to make I4.0 applicable to Indian industries. Marinagi et al. (2023) studied the KPIs responsible for supply chain issues and made a real identification of KPIs for supply chain 4.0.

Previous research has examined Industry 4.0 technologies in isolation (Frank et al., 2019; Ghadge et al., 2020), but few studies holistically assess their combined impact on sustainability in process industries. This study extends the Triple Bottom Line framework (Elkington, 1997) by integrating Industry 4.0 indicators, thereby providing a novel lens to evaluate how technological adoption aligns with economic, environmental, and social sustainability goals in resource-constrained settings. This study contributes novel methodological and contextual insights to the discourse on Industry 4.0. First, it pioneers the application of PLS-SEM in analyzing the combined effect of five distinct Industry 4.0 technologies on sustainability within India's process industries-a methodological advancement over prior studies that often focus on individual technologies or linear regression models. Second, it introduces a holistic dependent variable, Production Efficiency, Performance, and Sustainability (PEPS), which encapsulates operational, environmental, and social metrics, thereby bridging the gap between technological adoption and triple-bottom-line sustainability (Contini & Peruzzini, 2022). Third, the empirical focus on India provides region-specific insights, addressing the under-researched interplay of cultural, economic, and regulatory barriers unique to developing economies. These contributions fill critical gaps in the literature, offering a framework for global industries to replicate sustainable Industry 4.0 integration.

2.1 Industry 4.0 and Process Industry

The Fourth Industrial Revolution (4.0) involves the advancement and deployment of technologies across manufacturing and process industries. This transformation requires using IoT, AI, Big Data, and CPS within traditional industrial operations. The principal or central theory underlying Industry 4.0 is the idea of interconnected systems, in which machines, systems, and people work in synchrony. People are connected in this way thanks to IoT, which enables devices to share and gather information. Another reason for the system's enhancement is the use of real-time big data analytics. This system allows the development of processes and procedures that enhance operations. There are both opportunities and challenges that the proper implementation of Industry 4.0 poses for industries, specifically in process industries such as chemicals, pharmaceuticals, oil & gas, food & beverages, etc. Such industries are usually characterized by intricate production processes, strict compliance with legal requirements, and the need to control and manage numerous variables. Many of these complications can be gradually conquered through the implementation of Industry 4.0 technologies that will improve monitoring, control, and optimization.

One of the most significant advantages of Industry 4.0 for the process industry is the maximization of operational performance. New sensors and IoT devices enable real-time monitoring of production processes to maintain optimal conditions and identify deviations early. This information, when processed through in-house Big Data Analytics, enables the organization to perform maintenance on its assets before breakdowns, resulting in minimal interruptions to productivity. General production processes can also be enhanced by using patterns and predicting outcomes based on them through AI and machine learning algorithms. One pharmaceutical formulation process may be optimized by AI to achieve sustainable quality, whilst reducing wastage. Likewise, in the oil & gas industry, predictive modeling can improve reservoir management and drilling performance.

The other technology, Cyber-physical systems (CPSs), is also very important, as it combines physical working processes with computerized control mechanisms. They provide a virtual version of the physical process and enable all kinds of modeling and real-time changes to that modeling. Such interaction increases speed and flexibility and allows the process industry to respond quickly to changing market conditions and revised regulations. Alongside the benefits, certain issues, such as high implementation costs, the unavailability of qualified personnel, and data-related issues, hinder process improvements. All these issues can only be addressed through careful consideration of the challenges and options, including the step-by-step implementation. In this way, process sectors will unlock a higher level of competition, environmental health, and creativity. A total of six indicators are selected for the present study, which are shown in Figure 1.

Five indicators are selected as independent factors, and one is selected as the dependent factor. All these factors help to conduct the PLS-SEM-based study to find the impact of Industry 4.0 in the process industries.

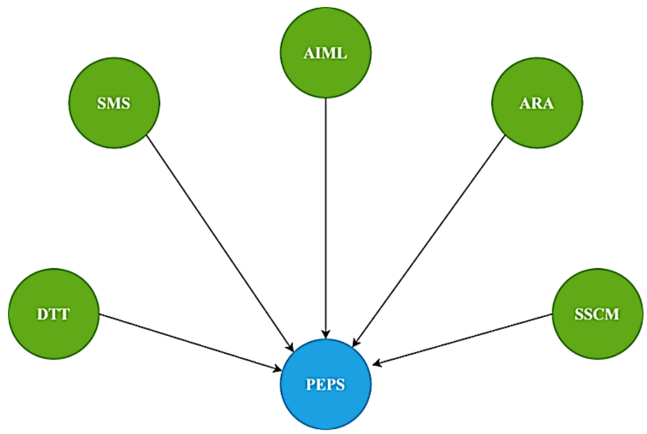

Figure 1. Initial path model for the present study.

2.2 Hypothesis Development

H1: An increase in productivity, performance, and sustainability (PEPS) in Indian process industries is largely contributed through the Smart manufacturing systems (SMSs).

The current hypothesis is based on extensive research and evidence that substantiates the impact, in particular, of SMS technologies on production systems in the context of the Fourth Industrial Revolution. Kamble et al. (2018) investigated the key D&Os for implementing I4.0 technologies in the Indian manufacturing industry, highlighting that smart manufacturing systems enhance both productivity and sustainability. Equally, Sahu et al. (2021) underscore that production systems embedded with AI ensure optimal production outcomes and usage efficiency, thereby justifying the original need for this hypothesis. The foregoing debate on the taxonomy of manufacturing systems also maintains the same view, supported by the work of Kagermann et al. (2013), which presents the strategic perspective of Industry 4.0 implementation as a game-changer for making production systems more agile and flexible.

In addition, Raj et al. (2020) further explored barriers to the adoption of Industry 4.0 technologies and stated that no barriers are insurmountable and that the adoption of smart systems increases production efficiency and performance. This is supported by Ghadge et al. (2020), who mentioned that SMSs within the purview of Industry

4.0 implementation are highly effective in enhancing supply chains and production processes, making them more sustainable. Thus, the H1: Smart manufacturing systems (SMSs) make a significant contribution towards improving production efficiency, performance, and sustainability of Indian process industries is well substantiated in the literature. It is equally important to highlight the same statement regarding the contribution of SMSs adoption toward the enhancement of the efficiency, performance, and sustainability of production systems, which is a core focus for the growth of the Indian process industries.

H2: In the Indian process industries, Digital Twin Technology (DTT) helps in increasing productivity, performance, and sustainability (PEPS) significantly.
Current Hypothesis H2, however, is supported by extensive literature showing the changing role of DTT across industries. Broadly, DTT enables the creation of virtual copies of existing physical objects, systems, or processes, allowing real-time monitoring, simulation, and optimization of production systems. Research conducted by Kamble et al. (2018) also found that the adoption of advanced digital technologies, including DTT, in Indian manufacturing addresses the major challenges and enhances business operational performance and sustainability. Through its capabilities for accurate monitoring and control, the DTT helps identify inefficiencies, prevent potential failures, and optimize maintenance plans, all of which contribute to enhanced operational effectiveness and performance. Such a proactive stance enables higher performance and prolonged optimal practice refilling by reducing wastage and energy loss.

Additional information concerning the application of AIMLs underscores the fact that calls for the embracement of the modern trends (DTT) qualify to yield better results in production metrics and in sustainability (Dalenogare et al., 2018). This is probably more so the case in Indian process industries, since efficient use of resources and reducing environmental damage are important objectives. Thus, the hypothesis “H2: Digital Twin Technology (DTT) improves the production efficiency, performance, and sustainability (PEPS) in Indian process industries” is well supported by the existing literature.

H3: The production efficiency, performance, and sustainability (PEPS) in the Indian process industries are significantly boosted with the use of Artificial Intelligence and Machine Learning (AIML).
The AIML technologies have been on the rise in recent decades and have become predominant in manufacturing transformation, especially in the scenario of Industry 4.0. In general, the adoption of AIML in Indian process industries can improve production efficiency, performance, and sustainability. As noted by Wang et al. (2016), AI-based analytics enables real-time decision-making, prescriptive rather than reactive maintenance, and optimal overall process management, thereby reducing downtime and improving outputs. AIML applications in manufacturing operations enhance quality management, materials use, and energy management, making manufacturing operations more sustainable (Sahu et al., 2021). Due to their predictive ability, AIML technologies help industries avert impending issues, and optimally use of resources to lessen waste and protect the environment. Even as they advance, the importance of these technologies in production systems increases for a competitive edge for Indian process industries.

H4: Advanced Robotics and Automation (ARA) enhances production efficiency, performance, and sustainability (PEPS) in Process Industries in India.
The ARA is one of the essential prerequisites for achieving the objectives of the Industry 4.0 Revolution. Hermann et al. (2016) stated that automation processes contribute to increasing the precision, consistency, and speed of production cycles. In the Indian context, Kamble et al. (2018) noted that integrating robotics and automation addresses labor shortages, enhances production efficiency, and lowers operating costs. Sophisticated autologous robotics allows individuals to safely and efficiently perform high-order activities with more efficiency and little human error. Furthermore, the deployment of ARA technologies also benefits sustainability and efficiency, not only in energy but also in material use, without compromising performance. Automation technologies are also supportive in the realization of the circular economy by further optimizing the recycling and reuse of materials, which enhances sustainability in process industries (Bonilla et al., 2018).

H5: Sustainable supply chain management (SSCM) greatly enhances production efficiency, performance, and sustainability (PEPS) in the Indian process industries.
The application of SSCM practices leads to effective waste management and improved supply chain flexibility in organizations (Raj et al., 2020). Companies can optimize waste generation, reduce greenhouse gas emissions, and meet compliance requirements by enhancing supply chain management information systems. Ghadge et al. (2020) further noted that such SSCM dialing directly

impacts the production efficiency and performance as eco-friendly materials, efficient logistics, and responsible procurement are employed. In addition, Bai et al. (2020) explain that the unification of SSCM disentangles collaboration with partners, resulting in greater innovation and sustainability. The process industries in India are under constant pressure to adopt sustainable practices, and therefore, implementing SSCM will ensure that the economic, environmental, and social goals are achieved.

3. Research Methodology

This study adopts a sectional research design to analyze the extent to which Industry 4.0 indicators influence sustainable production and performance in Indian process industries. The research applies a partial least squares structural equation modeling (PLS-SEM) analysis based on the relations of five independent latent variables: smart manufacturing systems (SMSs), digital twin technology (DTT), artificial intelligence and machine learning (AIML), advanced robotics and automation (ARA) and sustainable supply chain management (SSCM) towards the dependent latent variable of production efficiency, performance and sustainability (PEPS). Figure 2 presents the measurement and structural model, which is solved using the PLS-SEM method. Each independent latent variable has three observed variables, and one dependent latent variable has five observed variables. All these observed variables have been treated as questions and posed to the participants to obtain answers.

3.1 Data collection

The data for the current study were collected through a structured survey, in which questionnaires were sent to experts, engineers, managers, service providers, and stakeholders across different process industries in India. A total of 240 filled aspects were retrieved, contributing a rich data collection for analysis. The survey endeavored to evaluate the effects of Industry 4.0 technologies and practices on the production efficiency and sustainability of establishments.

3.2 Sampling Method

The approaches to goal-directed sampling focused on the inclusion of respondents who either took part in the practical implementation of the Industry 4.0 technologies or who possess knowledge of it. This strategy was adopted to take into account the views of a representative number of people in the workforce relevant to the implementation of technological innovations in the production processes. Purposive sampling helps mobilize respondents with knowledge in the study's fields, thereby increasing the study's accuracy.

3.3 Data Analysis

The analysis of the data collected from the field was conducted using SmartPLS software, which provides PLS SEM suitable for managing intricate structural designs. This method enables the direct and indirect relationships among all dimensions of PEPS to be mapped onto the indicator variables of Industry 4.0. The analysis involves

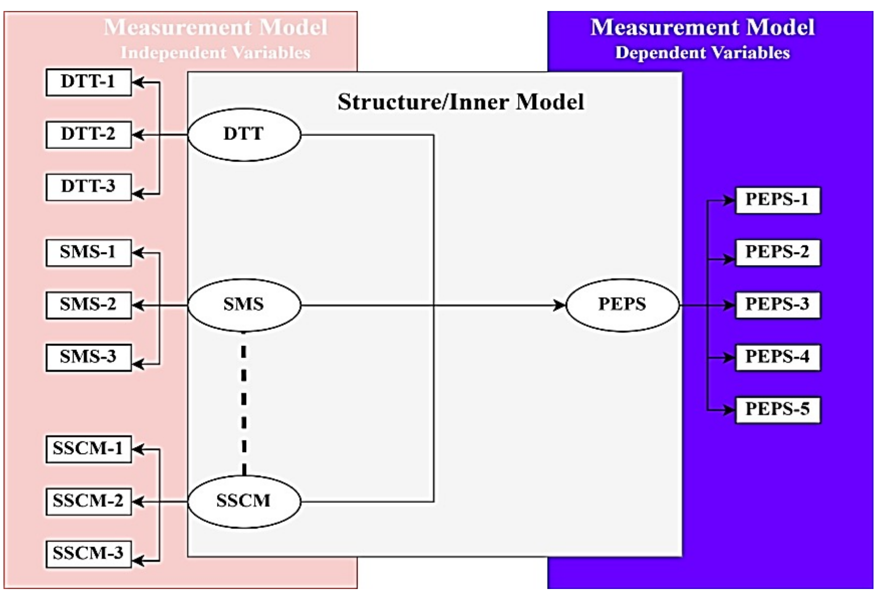

Figure 2. Measurement and structural model.

estimating the relationships in the measurement and structural models and evaluating the overall model's fit.

3.4 Validity and Reliability

In a bid to enhance the research findings, the study results are subjected to strict, specific validation measures, including assessments of both convergent and discriminant validity of the measurement model and the use of bootstrapping for hypothesis testing. These measures help establish the internal and external consistency of results.

The current methodology of the study aims to provide an understanding of how production efficiency and sustainability can be improved through the integration of Industry 4.0 technologies, thereby benefiting practitioners and policymakers. The first path model constructed in SmartPLS is shown in Figure 3. In this path model, the real observed variables are also seen. The initial path model can help to make the PLS SEM method for simulation and brainstorming analysis.

Data were collected via a rigorously validated questionnaire administered to 240 Industry 4.0 practitioners in Indian process industries. PLS-SEM was employed due to its predictive capabilities and suitability for exploratory research (Hair et al., 2019). The measurement model confirmed reliability (Cronbach's α >0.8) and validity (AVE >0.5), while bootstrapping (5,000 subsamples) validated the structural model's robustness, ensuring findings are both statistically significant and practically relevant. The PLS-SEM approach was selected for its robustness in handling complex structural models with latent variables and smaller sample sizes (Hair et al., 2019).

This method is ideal for exploratory research, as it prioritizes predictive accuracy over model fit, aligning with the study's goal of identifying key drivers of sustainability. The measurement model included three reflective indicators per independent construct (e.g., SMS, DTT) and five for PEPS, validated through rigorous reliability tests (Cronbach's α > 0.7, AVE > 0.5). Survey questions, designed on a 5-point Likert scale, were pre-tested with 30 industry experts to ensure clarity and relevance. Data from 240 respondents—managers, engineers, and stakeholders across pharmaceuticals, chemicals, and FMCG sectors—were analyzed using SmartPLS 4.0. Bootstrapping (5,000 subsamples) confirmed path significance, while HTMT ratios (<0.85) established discriminant validity. This methodological rigor ensures replicability and theoretical robustness.

3.5 Enhancing Data Collection Details

The survey instrument was structured into two sections: demographic profiling and construct-specific questions. Demographic data revealed that 68% of respondents held managerial roles, 22% were technical experts, and 10% represented policymakers, ensuring diverse perspectives. The questionnaire, distributed via email and in-person visits, underwent pilot testing to mitigate ambiguity and non-response bias. Common method bias was addressed using Harman's single-factor test (variance explained <40%). Constructs like SSCM included items on green

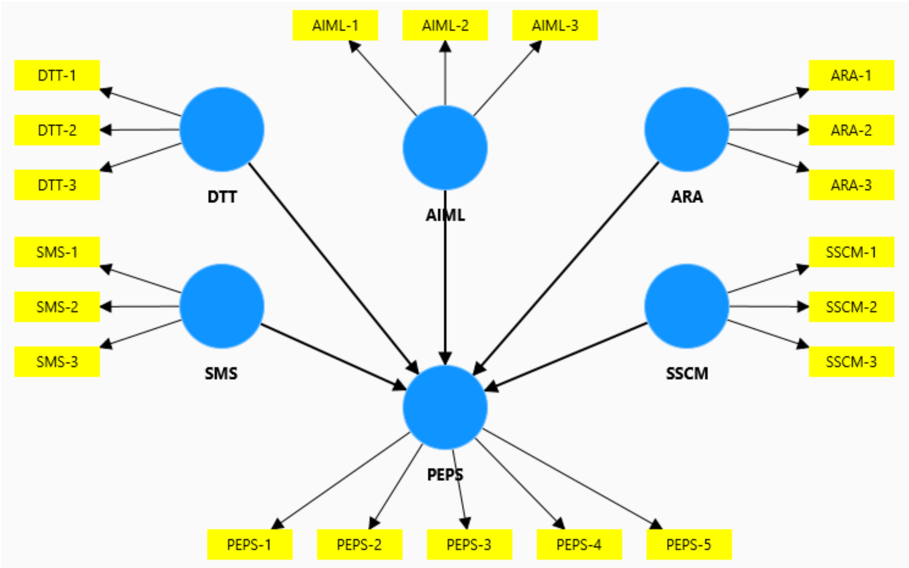

Figure 3. Initial path model developed for the present study.

procurement, carbon footprint reduction, and circular economy practices, aligning with Ghadge et al. (2020). Respondents represented mid-to-large enterprises, with 60% reporting partial Industry 4.0 adoption, primarily in automation and IoT. This granular detail strengthens the study's external validity and contextual relevance.

4. Results and Discussion

The implications of the measurement model assessment are particularly important for evaluating the reliability and validity of the constructs used in the study. Table 1 provides the values of Cronbach's alpha, the composite reliability (Rho_A and Rho_C), and the average variance extracted (AVE) for each of the latent variables: (DTT), (SMS), (AIML), (ARA), (SSCM), and (PEPS). All constructs have achieved a Cronbach's alpha for DTT of at least 0.768 and for PEPS of 0.926, which are very high, indicating internal consistency; the lowest is above the acceptable range of 0.7. The reliability of the constructs is further supported by the composite reliability (Rho_A and Rho_C) values, which also exceed the recommended threshold of 0.7. More specifically, satisfactory levels of Rho_C were observed for SMS (0.934) and SSCM (0.917), which highlights the sufficiency of the constructs for measuring the variables in concern. The AVE values for all constructs exceed the cutoff of 0.5, with AIML and SSCM relatively high at 0.836 and 0.839, respectively, indicating that the constructs account for most of the variance in the indicators.

These findings indicate that the measurement model is both dependable and trustworthy, reinforcing the proposition that constructs regarding the influence of Industry 4.0 indicators on sustainable production and performance within the Indian process industries are properly articulated and captured. It is plausible that very reliable and valid constructs will add confidence to the findings of this study regarding the capture of the relationship between the independent variable, Industry 4.0 indicators, and the dependent variable PEPS. This ease of reliably measuring the constructs enhances the extent to which the study found support for the assertion made about the influence of Industry 4.0 technologies on the production and performance of Indian process industries. Such results foster further examination by allowing the optimum forms devoid of waste, Fisher's designs, and general performance due to this improvement. Table 2 presents the HTMT analysis of the constructs, including information on the type of ratio, which may be neglected in such analysis, among several particulars reported for the constructs. It is a necessary condition for proving that

Table 1. Results generated for the measurement model.

Parameters	Cronbach's Alpha	Composite reliability (Rho_A)	Composite reliability (Rho_C)	AVE
DTT	0.768	0.786	0.827	0.794
SMS	0.869	0.871	0.934	0.824
AIML	0.907	0.924	0.879	0.836
ARA	0.786	0.805	0.907	0.767
SSCM	0.814	0.837	0.917	0.839
PEPS	0.924	0.867	0.897	0.739

Table 2. HTMT analysis for the present study.

Parameters	DTT	SMS	AIML	ARA	SSCM	PEPS
DTT						
SMS	**0.863**					
AIML	0.725	**0.832**				
ARA	0.697	0.811	**0.764**			
SSCM	0.804	0.689	0.714	**0.814**		
PEPS	0.768	0.751	0.627	0.784	**0.759**	

all constructs present in the model under consideration measure different things.

The HTMT values calculated across the constructs do not exceed the stringent upper limit of 0.90, indicating that the constructs are adequately separated from one another. For instance, the HTMT value for the cohesion between DTT and SMS is 0.863, indicating a clear linkage despite some differences. Likewise, regarding ARA and SSCM, their HTMT interrelationships are considered valid, with a value of 0.814. Also, there are relatively low HTMT values, such as 0.627, between AIML and PEPS, indicating that these constructs are related within the model. These findings validate that the constructs used to measure the impact of Industry 4.0 indicators on sustainable production and performance within Indian process industries are not only reliable but also adequately differentiated. The HTMT analysis helps finalize the model by confirming the relationships among the variables, thereby instilling confidence in the results.

This allows concluding that the relationships described in this study do exist, and that the Industry 4.0 indicators and any of their sub-systems have a significant influence on production efficiency, performance and sustainability for the Indian process industries context. The analyses of hypothesis testing that has been presented in Table 3 facilitates a greater understanding of the relationship that exists between the Industry 4.0 indicators and sustainable production and performance in Indian process industries towards meeting predefined standards. Key statistical parameters, which include the original sample, sample mean, standard deviations, T value, P value, and effect size, are used in assessing each hypothesis.

All five hypotheses, i.e., H1 to H5, discuss significant relationships with *P*-values below the conventional cut-off of 0.05. The *t* values, which measure the strength of these relationships, are greater than 2 in all cases, indicating statistically significant findings. For instance, Hypothesis H2 has a T value of 7.35 and a P value of 0.001, indicating that smart manufacturing systems (SMSs) exert a strong and significant influence on productivity, performance, and sustainability (PEPS), with an effect size of 0.207. According to the study, hypothesis H5 is the most dominant from the perspective of T value equal to 9.12 and P value equal to 0.000, and the goal among the rest which considers the effect size of 0.268, meaning that there's a high level of interrelationship between sustainable supply chain management practices and efficient performer business PEPS model. The study indicates that SSCM is an integrative approach that helps to achieve the objective of upscaling green production and performance. Further, the analyses have established that all DTT, MIV, AIML, ARA, and SSCM factors are of great concern in the context of Industry 4.0 and have a positive impact on PEPS, but with a moderate effect size. This difference in effect sizes indicates how each impact indicator should be prioritized in terms of sustainable outcomes. These findings are one of the most recent with respect to the use of various strategies of Industry 4.0 technologies to improve production and performance in Indian process industries.

5. Conclusion

The present research concluded that advanced technologies play an important role in improving production efficiency, performance, and sustainability in process industries. The study of key aspects of Industry 4.0, such as DTT, SMS, AIML, ARA, and SSCM, enables the identification of a generally positive effect of these technologies on the performance of Indian process industries. The measurement model analysis provides ample evidence supporting the reliability and validity of the study's variables. The internal consistency of the response factors, composite reliability, and average variance extracted (AVE) are high for all factors, indicating that the selected measures are reliable. Further confirming the study's findings is the HTMT analysis, which clearly indicates strong discriminant validity among the constructs, such that each technology contributes additively to the model. The

Table 3: Hypothesis testing analysis for the present study.

Hypothesis	Original Sample	Sample Mean	STDEV	T Value	P Value	Effect Size
H1	0.339	0.314	0.124	4.62	0.010	0.142
H2	0.351	0.347	0.106	7.35	0.001	0.207
H3	0.307	0.325	0.098	3.46	0.024	0.128
H4	0.365	0.437	0.091	5.37	0.001	0.216
H5	0.287	0.343	0.118	9.12	0.000	0.268

hypothesis testing analysis and the relationships within and across statements illustrate that all 5 dimensions of Industry 4.0 significantly contribute to producing and performing sustainably, though the effects differ in extent. Among these, SSCM has emerged as the most influential factor, underscoring the importance of integrating environmental concerns into supply chain management. The strong impact of SMSs and ARA also highlights the critical role of automation and smart manufacturing systems in improving performance and efficiency.

The present investigation suggests that the Indian process industries cannot ignore the adoption of Industry 4.0 technologies to achieve sustainable production and performance. This study will also help practitioners and policymakers emphasize the importance of allocating funds for these advanced technologies to remain competitive in global markets and achieve sustainable development. It also stresses the need for further studies on this topic to be conducted in the future on the challenges faced in the adoption of these technologies and their impact over time in various industries.

Conflict of interest

The authors have no conflict of interest to declare.

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