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ORIGINAL RESEARCH

Factors Influencing the Implementation of Industry 4.0 for Sustainability in Manufacturing

Veepan Kumar[1] · Prem Vrat[2] · Ravi Shankar[3]

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Abstract *Digital transformation leveraging Industry 4.0 is referred to as a strategic solution to handle the challenges given by growing competition and unpredictable customer demands in today's highly competitive business environment. However, transitioning to Industry 4.0 for sustainable manufacturing would require a thorough understanding of key implementation factors. The objective of this paper is to examine and validate the interrelationships among the factors influencing the implementation of Industry 4.0 for achieving sustainability in manufacturing. To accomplish this objective, the paper used an integrated methodological approach (i.e., TISM and PLS-SEM) to model the factors influencing Industry 4.0 implementation. The total interpretive structural equation modeling (TISM) technique was used to develop the hierarchical structural model in order to investigate the interrelationships among the Industry 4.0 implementation factors. The partial least squares structural equation modeling (PLS-SEM) approach was used to validate the interrelationships identified through TISM. Initially, implementation factors of Industry 4.0 for sustainable manufacturing have been identified. Following the identification of the factors, the opinion of experts was sought through a questionnaire-based survey to finalize them. The hypotheses were analyzed to test the significance of interrelationships among different constructs of Industry 4.0 factors. The findings indicate that factors like environmental regulations for sustainability, adequate labor laws for workforce working in the digital environment, continuous support and commitment from top management, effective restructuring of the organization, adequate support from different stakeholders, and strategic roadmap for digital transformation and branding of green image have the maximum influence on Industry 4.0 implementation for sustainability. Furthermore, the obtained results were in accordance when validated using PLS-SEM. This research will assist practitioners in gaining a thorough understanding of the significance of various implementation factors and their interrelationships.*

Keywords Implementation factors · Industry 4.0 · PLS-SEM · Sustainable manufacturing · TISM

✉ Veepan Kumar
veepan.kumar@fsm.ac.in; vkiit1234@gmail.com

Prem Vrat
premvrat@gmail.com; profpremvrat.iitd@gmail.com

Ravi Shankar
ravi1@dms.iitd.ac.in

[1] Quantitative Techniques and Operations Management (QT-OM) Area, FORE School of Management, New Delhi, India

[2] School of Management, The NorthCap University, Sector 23A, Gurugram, Haryana, India

[3] Department of Management Studies, Indian Institute of Technology, New Delhi, Delhi, India

Introduction

Today's business environment is volatile, uncertain, complex, and ambiguous (Kumar et al., 2021a). As a result, to survive in this scenario, manufacturing organizations need to ensure sustainability as per the Triple bottom line (TBL) perspectives while producing and delivering the products to end customers. Three TBL dimensions, according to Machado et al. (2020), are (a) manufacturing a product with a higher return on investment for better economic benefits, (b) manufacturing environmentally friendly products to reduce environmental deterioration impacts, and (c) developing a creative working environment among workers to encourage innovation, learning, and collaborative culture. Among these three TBL dimensions mentioned, environmental protection has been identified as the most influential variable by various environmental agencies, non-governmental organizations (NGOs), and policymakers (Ghosh et al., 2020).

Increased globalization pressures and demand for high-quality goods have resulted in overconsumption of natural resources, putting the environment at risk due to massive industrial waste and toxic emissions generation. For example, among various manufacturing-related wastes, electronic and electrical waste has emerged as one of the fastest-growing wastes in recent years. In this regard, extended producer responsibility (EPR) has been introduced and adopted as a key regulatory directive to address e-waste control and reduction (Wang et al., 2017; Zeng et al., 2016). This regulatory requirement would ensure sustainability by reducing hazardous industrial waste, lowering greenhouse gas emissions, and ensuring employee health and safety. Due to an inconsistency between the three dimensions of TBL, manufacturing companies face multiple challenges in terms of overall sustainable growth and development in the real industrial scenario (Ivascu, 2020). As a result, adopting an adequate regulatory mechanism is essential for organizational sustainability.

During past industrial revolutions, organizations were solely concerned with achieving economic gains/benefits, with complete disregard for environmental sustainability (Ramirez-Peña et al., 2020). Furthermore, according to Bag et al. (2021), previous industrial revolutions have ignored sustainability in two dimensions (i.e., social and environmental) while manufacturing and delivering products to end customers. Manufacturers are currently under immense pressure to comply with stringent environmental regulations levied by governments and numerous environmental agencies worldwide. As a result, companies must modernize their manufacturing systems by emphasizing the implementation of recent eco-innovations that can improve the environment and social dimensions while also providing economic benefits (Gbededo et al., 2018). In today's volatile business world, manufacturing companies have not only to satisfy growing customers' needs toward customized products but also to satisfy the ever-increasing demand toward environmentally sustainable as well as economically efficient products (Sassanelli & Terzi, 2022; Stock & Seliger, 2016). In recent times, the concept of Industry 4.0 has emerged as a feasible option with strong implications for manufacturing competitiveness and sustainability through digital advancement (De Sousa Jabbour et al., 2018a). The term Industry 4.0 refers to the fourth industrial revolution, which describes the recent technological changes that the manufacturing industry is experiencing in terms of the emergence of new business models and digitalized value chains based on enabling digital technologies (Büchi et al., 2020). This high-tech concept was introduced by the German Federal Ministry in 2011 (Umar et al., 2021) as part of a strategic project aiming to digitalize the manufacturing sectors through empowering innovative technologies (Kagermann et al., 2013).

The enabling technologies of Industry 4.0 like the Internet of Things (IoT), cloud computing, big data analytics, cybersecurity, simulation, autonomous robotics system, etc. (Bai et al., 2020; Dalenogare et al., 2018; Mbakop et al., 2022) are anticipated to play a critical role in executing sustainable industrial decisions (Kamble et al., 2018). This may include environmental design (i.e., designing goods for longer life cycles focused on the 5Rs approach (i.e., reduce, repair, re-use, recycle, and remanufacture), cleaner manufacturing (i.e., regulated production and consumption with minimal waste), and effective logistics route planning (de Sousa Jabbour et al., 2018). Furthermore, these digital technologies can make significant contributions to an organization's sustainable development and competitiveness (Mabkhot et al., 2021; Stanisławski & Szymonik, 2021). Essentially, Industry 4.0 technologies would digitally, horizontally, and vertically integrate the physical and virtual worlds (Acioli et al., 2021), implying that physical resources such as actuators, sensors, and microcontrollers would be digitally connected via the Internet of Things (IoTs) and Cyber-physical systems (CPS).

Different operational areas of the current industrial ecosystem are anticipated to change as a result of Industry 4.0 technologies, becoming self-regulating, intelligent, self-optimizing, and self-adapting systems. The rising market demand puts pressure on industrial systems' energy needs, jeopardizing environmental efficiency and potentially creating a vicious spiral in a globally competitive world. Thus, practitioners regard Industry 4.0 as a distinct industrial wave that will drastically transform manufacturing systems in order to boost organizational efficiency by reducing waste and reducing the repetitive nature of tasks/work. In today's volatile business environment, digital technologies, sustainability, and digital collaboration are receiving a lot of attention because of the potential consequences of Industry 4.0 for sustainable development (Toktaş-Palut, 2022). Manufacturing companies are currently struggling to implement Industry 4.0 for achieving sustainability as TBL perspectives due to a variety of challenges that, if not addressed properly, will lead to failure in the pre- and post-implementation stages. The challenging factors can thus be successfully mitigated by identifying and comprehending various factors influencing

Industry 4.0 implementation (i.e., enablers/drivers/critical success factors). Furthermore, it is critical to investigate the dynamics and interrelationships of these variables so that the nature of their influence can be recognized for successful implementation.

There are many studies that focus on examining the enablers/drivers/success factors/drivers of Industry 4.0 (Adebanjo et al., 2021; Contador et al., 2020; Devi et al., 2021; Jain & Ajmera, 2021; Krishnan et al., 2021; Murugaiyan & Ramasamy, 2021). However, in the past literature, there tends to be a scarcity of scholarly studies that attempt to examine the connection between sustainability and Industry 4.0 (Bai et al., 2020) adequately through analyzing their enablers/critical success factors/drivers (Ghobakhloo, 2020; Harikannan et al., 2020; Luthra et al., 2020; Yadav et al., 2020). For example, Ghobakhloo (2020) looked at the interrelationships among Industry 4.0 functions to achieve sustainability in manufacturing using ISM-MICMAC. Harikannan et al. (2020) used ISM-MICMAC to analyze the drivers of sustainable Industry 4.0. Luthra et al. (2020) employed Grey-DEMATEL to investigate the cause–effect interactions of Industry 4.0 drivers for obtaining sustainable benefits in the supply chain. Yadav et al. (2020) used the Robust Best Worst Method (RBWM) to measure the strength of each Industry 4.0 enabler's influence on achieving sustainability in manufacturing organizations. These studies (Ghobakhloo, 2020; Harikannan et al., 2020; Luthra et al., 2020; Yadav et al., 2020) focused solely on examining the enablers' interrelationships, measuring the enablers' influence, and investigating the casual relationships among enablers/drivers. According to Harikannan et al. (2020), future research should incorporate more drivers/enablers to examine Industry 4.0 comprehensively. Therefore, it can be concluded from prior research that little systematic work has been done on assessing the significance of interrelationships of Industry 4.0 enabling variables for achieving sustainability in Indian manufacturing firms through statistical validation. This research gap has been addressed in this paper by developing and statistically validating a hierarchical structural model for Industry 4.0 to achieve sustainability benefits by considering a greater range of implementation factors. Furthermore, there aren't many studies that look at all three of the TBL dimensions of Industry 4.0 technologies simultaneously. Based on these research gaps, this study intends to contribute to the literature on Industry 4.0 by answering the following Research Questions (RQs):

RQs What are different factors influencing the implementation of Industry 4.0 to achieve sustainability in a manufacturing organization?; How could the mutual interrelationships existing for these factors be examined and statistically validated for Industry 4.0 effective implementation?

To address the above research questions, the following research objectives (RO) was formulated:

- To identify various factors influencing Industry 4.0 implementation in the manufacturing organization in order to achieve sustainability
- To analyze the interrelationships among the selected factors of Industry 4.0 implementation using total interpretive structural modeling (TISM)
- To validate the relationships of factors derived from the TISM hierarchical structural model using Partial least square-structural equation modeling (PLS-SEM)

To accomplish the objectives mentioned above, the present paper proposes an integrated TISM and PLS-SEM model. TISM is a newer variant of the ISM methodology that incorporates a systematic approach to provide a decision-maker with a comprehensive explanation of the interrelationships at the nodes and links. PLS-SEM is used in this research to test the significance of the structural relationship between the factors. Thus, this study tries to prove the main hypothesis which states that the factors of Industry 4.0 implementation are positively interrelated with one another. While these two techniques have been used in a few studies separately, no attempt has been made to combine the PLS-SEM approach with the TISM methodology for analyzing the Industry 4.0 implementation variables for Indian manufacturing organizations.

The rest of the paper is structured as follows. Section 2 gives an overview of the literature related to Industry 4.0 and sustainability, followed by identification of the implementation factors, and in the end, research gaps identified from the past studies have been elaborated. Section 3 highlights the research methodology used in this research. Section 4 describes the research methodology (TISM and PLS-SEM) application to analyze Industry 4.0 implementation for sustainable manufacturing. The findings of the paper are explained in Sect. 5. Sections 6 and 7 present the theoretical and managerial implications for researchers, practitioners and stakeholders, while Sects. 8 and 9 explore the paper's conclusions, limitations, and future scope.

Literature Review

This part of the paper is divided into three sections, the first of which addresses the contributions of various researchers to Industry 4.0 implementation for achieving sustainability in manufacturing organizations. The second sub-section presents the twenty-three Industry 4.0 implementation factors for achieving sustainability in industrial organizations, derived from a literature review and subsequent discussion with experts. The study's research gaps are discussed in the third sub-section.

Review of Literature on Industry 4.0 for Sustainability in Manufacturing

With a better understanding of sustainability issues, practitioners are more concerned about making industrial practices sustainable for people's social well-being (social), environmental prosperity (environment), and company's economic development (economic) (Sikdar et al., 2017). The term sustainability refers to meeting the needs of current generations without jeopardizing future generations' ability to meet their own needs (Belaud et al., 2019). According to Junior et al. (2018), major social themes such as "environmental protection" and "process safety" have gained widespread attention from practitioners as a result of a plethora of environmental forums, climate campaigns, and agreements held around the globe. The emphasis on improving manufacturing productivity through digitalization became a reality with the introduction of the high-tech concept (i.e., Industry 4.0) announced by the German government in 2011 (Kagermann et al., 2013). The concept of sustainability appears to be a complex issue due to maintaining a proper balance between the three TBL dimensions while redesigning the organization's strategy toward sustainable practices (Gupta et al., 2021). The imbalance between the three TBL dimensions would result in several issues, the most serious of which would be land degradation, global warming, and severe environmental disasters (Lupi et al., 2022). However, some researchers have concluded that organizations should pursue eco-friendly practices and successfully comply with government legislation on these activities to gain a potential competitive advantage in today's new business trend. The manufacturing industry is currently undergoing the most recent high-tech industrial transition (i.e., Industry 4.0), which aims to reconfigure the entire production system with innovative technologies. Each Industry 4.0 technology is expected to function in such a way that their holistic integration (horizontal, vertical, and end-to-end digital) allows manufacturing systems to ensure competitiveness and sustainability. Thus, several researchers began to investigate the capabilities of Industry 4.0 in order to reap sustainability benefits in the manufacturing and supply chain. Only a few researchers have tried to establish a link between Industry 4.0 and sustainability either through narrative literature reviews (Ejsmont et al., 2020; Kamble et al., 2018; Machado et al., 2020; Sharma et al., 2020) or exploratory (qualitative) studies (de Sousa Jabbour et al., 2018).

Furthermore, there has been a lack of clarity in the views/statements of different scholars when drawing the concluding remarks on the relationship/interface between Industry 4.0 and sustainability in previous literature studies (Ching et al., 2021; Li et al., 2020). Few researchers, for example, believe that implementing Industry 4.0 would disrupt the organization's sustainability while producing the products and services. According to Tseng et al. (2018), Industry 4.0 technologies would require a large amount of resources and energy to work and operate, resulting in various adverse environmental effects such as global warming and climate change. Furthermore, some researchers (Dalenogare et al., 2018; Kiel et al., 2017) believe that Industry 4.0 would negatively impact product quality and result in financial and environmental pressures. According to Luthra and Mangla (2018), these technological advancements would have a negative impact on employees' health and safety. In contrast, the majority of researchers believed that Industry 4.0 would enhance the sustainability of manufacturing organizations. The disparity in researchers' perspectives is primarily due to a misunderstanding of the relationship between Industry 4.0 and sustainability.

The practitioners describe Industry 4.0 as a modern industrial revolution that is digitally changing the industrial landscape to improve productivity, efficiency, and competitiveness of various industrial processes (Kumar et al., 2022). On the other hand, the researchers regard Industry 4.0 solely from a technical standpoint within the Information Technology Domain. In contrast, the topic of sustainability/sustainable supply chain/sustainable production is debated in the domain of business management (Bag et al., 2021). These two themes are mutually reinforcing, and their ability to transform manufacturing practices is dependent on the amalgamation of core concepts such as remanufacturing, design for circularity and regenerative, design for disassembly, circular supply chain management, and ergonomic design for a sustainable workplace for improving employee health and safety (Duarte & Cruz-Machado, 2017; Teknikföretagen, 2017; Waibel et al., 2017). The research on the impact of Industry 4.0 on organizational sustainability is still in its early stages, and the consequences of Industry 4.0 in terms of economic, environmental, and societal implications on the manufacturing system need to be investigated further. To address these concerns, the present study is based on the assumption that implementing Industry 4.0 would improve the sustainability of manufacturing systems. As a result, the present study seeks to identify and analyze the factors that influence Industry 4.0 implementation in order to achieve sustainability in manufacturing organizations. Some articles in the literature investigate the implications of Industry 4.0 for achieving manufacturing sustainability by examining the impact of digital technologies and implementation elements known as Industry 4.0 influencing factors/

enablers/drivers. The following articles are discussed briefly below:

Ching et al. (2021) used the ISM approach to recognize the interrelationship of Industry 4.0's sustainability functions. Later, based on the ISM findings, a roadmap for attaining sustainable manufacturing using digital technologies of Industry 4.0 was proposed. According to the findings, 'safe and smart working environment' and 'supply chain integration' are critical functions for achieving sustainability advantages based on Industry 4.0 technologies. Bai et al. (2022) proposed a framework based on the DEMATEL approach to investigate the impact of Industry 4.0 technologies on sustainable development goals (SDGs) while taking circular economy concepts into account. They concluded that autonomously dismantling for electronics is most appropriate for digital technologies to achieve social sustainability through the CE strategy. Bai et al. (2020) used the VICKOR approach to understand the consequences of Industry 4.0 technologies for the organization's sustainable development by considering hesitant fuzzy sets and cumulative prospect theory. They concluded that the technological pillars of Industry 4.0, such as simulation, drone technology, and mobile technology, have the maximum influence on sustainability in various industrial segments such as electronics, automotive, food and beverage, textile, clothing, and footwear. de Sousa Jabbour et al. (2018) proposed a framework for understanding the convergence of Industry 4.0 and environmental sustainability in manufacturing, focusing on eleven critical success factors (CSFs). Harikannan et al. (2020) used interpretive structural modeling (ISM) and the MICMAC approach to examine the twenty drivers for integrating Industry 4.0 and sustainable manufacturing. Yadav et al. (2020) ranked the enablers of Industry 4.0 technologies to achieve sustainability in the manufacturing organization using the robust best–worst method. They found that the categories of managerial, economic, and environmental enablers had the most significant influence on achieving sustainability through the implementation of Industry 4.0. Ghobakhloo (2020) examined the interrelationships among the sixteen Industry 4.0 functions to achieve sustainability in the manufacturing industry using the ISM-MICMAC methodology. Luthra et al. (2020) investigated the cause-and-effect relationship between various identified Industry 4.0 drivers for supply chain (SCs) sustainability using the Grey-DEMATEL approach. Their findings indicate that adequate government policies and cooperation, and transparency among supply chain stakeholders are the two most important drivers of Industry 4.0.

Bag et al. (2021) conducted a comprehensive literature review to recognize Industry 4.0 enablers for supply chain sustainability. Chauhan et al. (2019) proposed the SAP-LAP linkage framework to understand better Industry 4.0 and the Circular Economy (CE). According to the findings, top management is the most important actor in implementing Industry 4.0 to achieve CE benefits in the manufacturing enterprise. Shayganmehr et al. (2021) used the Fuzzy Delphi approach and an Analytical Hierarchy Process (AHP) focused on Interval-Valued Fuzzy Sets (IVFS) to verify and prioritize the identified Industry 4.0 technology enablers for cleaner manufacturing and circular economy activities in the light of ethical and sustainable business growth. Their findings indicate that technical competence is the most critical enabler for long-term sustainable development. Stock and Seliger (2016) describe the prospects and possibilities for sustainability offered by Industry 4.0 from a macro- and micro-perspective. Thus, it can be deduced that successful implementation of Industry 4.0 would result in a variety of benefits from the perspective of TBL. However, a number of issues arise during implementation. Data ownership and privacy issues, insufficient environmental regulations, a lack of labor laws for a less skilled workforce, a lack of a strategic roadmap, and high implementation costs are just a few examples (Kumar et al., 2021; 2021a). These issues must be addressed systematically. In this regard, the present study identified the factors of Industry 4.0 implementation for manufacturing sustainability and modeled them to analyze and validate their interrelationships.

Identification of Industry 4.0 Factors

To gather information on the factors of Industry 4.0 implementation, electronic databases such as Scopus, Science Direct, and Web of Science were used. The following keywords were entered into the search: Industry 4.0/smart manufacturing/digital manufacturing and influencing factors/enablers/critical success factors/ drivers and sustainability/sustainable development. Table 1 shows the list of the twenty-three factors that were identified as a result of the extensive literature review.

Research Gaps in the Literature

The following research gaps have been identified based on the literature review of Industry 4.0 enablers/drivers/influencing factors for sustainability in manufacturing.

Several studies in the past literature have outlined the drivers/enablers/critical success factors of Industry 4.0 implementation across manufacturing organizations (Adebanjo et al., 2021; Devi et al., 2021; Jain & Ajmera, 2021; Krishnan et al., 2021; Murugaiyan & Ramasamy, 2021). However, only a few studies have identified influencing factors/enablers/CSFs/drivers/functions of Industry 4.0 implementation for achieving sustainability in manufacturing and supply chains (Ghobakhloo, 2020; Harikannan

Table 1 List of factors identified for Industry 4.0 implementation in order to achieve sustainability in manufacturing

Sr. no	Factor name	References
F1	Continuous support and commitment from top management	Bag et al. (2021), Chauhan et al. (2019), de Sousa Jabbour et al. (2018), Luthra et al. (2020), Sony and Malik (2020b)
F2	Strategic roadmap for digital transformation and branding of green image	Bag et al. (2021), de Sousa Jabbour et al. (2018), Ghobakhloo (2018)
F3	Effective restructuring of the organization	Bag et al. (2021), de Sousa Jabbour et al. (2018), Rojko (2017), Sony and Malik (2020b)
F4	Adequate digital infrastructure	Chauhan et al. (2019), Luthra et al. (2020)
F5	Environmental regulations for sustainability	Chauhan et al. (2019), Luthra et al. (2020)
F6	Adoption of digital technologies of Industry 4.0	Xu et al. (2018)
F7	Digital culture of innovation and sustainability	Nafchi and Mohelská (2020)
F8	Employee empowerment and commitment	de Sousa Jabbour et al. (2018)
F9	Effective implementation of Industry 4.0	Stock et al. (2018), Vaidya et al. (2018)
F10	Robust cybersecurity mechanisms for data theft issues	Babiceanu and Seker (2017); Lezzi et al. (2018)
F11	Horizontal, vertical, and end-to-end digital integration	Kamble et al. (2018)
F12	Up-skilling of the workforce	Bag et al. (2021), de Sousa Jabbour et al. (2018), Sony and Malik (2020b)
F13	Lean production through lead time reduction	Dalenogare et al. (2018)
F14	Research and development for developing technologies indigenously, technical standards and reference architecture	Bag et al. (2021), Xu et al. (2018)
F15	Customer satisfaction	Witkowski (2017)
F16	Sustainability through controlled consumption	de Sousa Jabbour et al. (2018), Kamble et al. (2018)
F17	Adequate support from different stakeholders	Bag et al.(2021)
F18	Flexible and mass customized production	Fatorachian and Kazemi (2018), Helo and Hao (2017)
F19	Evaluation of an organization's readiness toward Industry 4.0	Sony and Naik (2020a)
F20	Technological incentives and rewards to the employees	Lin et al. (2018), Stock and Seliger (2016)
F21	Improved health and safety of employees	Kamble et al. (2020), Müller et al. (2018)
F22	Adequate labor laws for workforce working in the digital environment	Bag et al. (2021), Krishnan et al. (2021)
F23	Effective regulations/norms for security of data/information	Maarouf (2018), Sony and Malik (2020b)

et al., 2020; Luthra et al., 2020; Yadav et al., 2020). Ghobakhloo (2020) attempts to investigate the interrelationships between the sixteen Industry 4.0 functions for achieving sustainability in the context of developing-country manufacturing organizations. Harikannan et al. (2020) examined twenty drivers of sustainable Industry 4.0 in the context of manufacturing organizations in developing countries like India. Luthra et al. (2020) used Grey-DEMATEL to explore the cause–effect interrelationship of major drivers of Industry 4.0 to achieve sustainable benefits in supply chains from a TBL viewpoint in developing countries like India. Yadav et al. (2020) used the Robust Best Worst Method (RBWM) to determine the intensity of influence of each Industry 4.0 enabler on achieving sustainability in manufacturing organizations in developing countries like India. As a result, it is evident from these studies that the significance of interrelationships between different enablers/drivers/factors of Industry 4.0 has not been empirically validated. Furthermore, Harikannan et al. (2020) suggest that more drivers be included in future studies while developing the hierarchical structural model so that the utility of exploratory research could be improved. Validating the interrelationships of Industry 4.0 implementation factors captured via the TISM/ISM model using structural equation modeling (SEM) methodology has also been suggested as a future scope in the literature. The present study addresses these gaps by developing a hierarchical structural model for Industry 4.0 to achieve sustainability benefits by considering a greater range of implementation factors. Further, the interrelationships of factors recognized through the developed TISM model have been statistically validated using the partial least square structural equation modeling (PLS-SEM) approach.

Research Methodology

The present study has used an integrated TISM and PLS-SEM methodological approach to accomplish the objectives specified for this study. The main motivation for integrating the two methodologies is to better comprehend the complex and dynamic relationships (both qualitatively and quantitatively) that exist among various influencing variables to implement Industry 4.0. Various researchers have successfully applied these two approaches (i.e., ISM/TISM and SEM) in a variety of fields, including mass customization in Indian SMEs (Ullah & Narain, 2021), sustainable supply chain management (Gardas et al., 2019), lean business implementation (Jasti & Kota, 2021) and sustainable lean six sigma (Swarnakar et al., 2020).

To the best of our knowledge, no approach based on integrated TISM and PLS-SEM methodology has been developed for modeling and validating the interrelationships of Industry 4.0 implementation factors in manufacturing organizations to achieve sustainability. Figure 1 shows the research design used to model the Industry 4.0 implementation factors. In the following sections, each methodology has been thoroughly discussed:

Total Interpretive Structural Modeling (TISM)

John N. Warfield proposed Interpretive Structural Modeling (ISM) in 1973 to investigate complicated relationships between variables using a graphical representation of a systematic hierarchical diagram known as a structured model. ISM used graph theory to investigate the interrelationships between variables in the complex system. The ISM method's main weakness is that it disregards the justification of the variables at the links. As a result, the limitations of the ISM approach have been eliminated by upgrading it to TISM. TISM is the most recent extension of ISM that uses a hierarchical diagram to handle an unstructured problem and is capable of answering basic theory-building questions like "what," "how," and "why" which are critical for any research conceptualization phase (Sushil, 2012, 2018; Sushil & Dinesh 2022). In TISM, an interpretive matrix is a one-of-a-kind tool that serves as the foundation for a knowledge base of interpretive logic. The applications of ISM/TISM can be found in a wide range of research fields including, end-of-life tire management (Kannan et al., 2014), port logistics (Sarkar & Shankar, 2021), lean–agile manufacturing (Narkhede et al., 2020), waste management (Singh & Sushil, 2017), humanitarian supply chains (Yadav et al., 2016) and flexible manufacturing system (Dubey & Ali, 2014; Dwivedi er al., 2021). The procedure used to develop the TISM model is discussed in Sect. 4.2.

Questionnaire-Based Survey

A questionnaire-based survey was conducted to learn about different practitioners' perceptions on the significance of Industry 4.0 implementation factors for Indian manufacturing companies' sustainability. The survey was created in Microsoft Form and emailed to different Indian manufacturing companies in the northern (Delhi, Haryana, and Punjab), southern (Karnataka), and western (Maharashtra and Gujarat) regions of the country. It is split into two sections: the first collects demographic information from respondents, and the second assesses the importance of Industry 4.0 implementation factors using a five-point Likert scale. The survey's application is discussed in Sect. 4.1.

PLS-SEM

Structural equation modeling (SEM) is a statistical method for modeling, estimating, and testing the significance of interrelationships between measurable and latent variables. According to previous literature studies, researchers use two types of structural equation modeling: (a) variance-based partial least squares structural equation modeling (PLS-SEM) and (b) covariance-based structural equation modeling (CB-SEM). The former is suitable for analyzing both small sample sizes and complex theoretical models (i.e., possessing the large number of items and constructs) (Hair et al., 2017). The latter, on the other hand, is appropriate for analyzing models of large sample sizes. PLS-SEM has a higher predictive ability than CB-SEM, which is especially useful when conducting exploratory research in less developed or emerging subjects (Ringle et al., 2012). Thus, the use of PLS-SEM in this study is justified, given that the research area (Industry 4.0) is still in its infancy in terms of investigating implementation factors. There are two critical steps to take while performing the PLS-SEM analysis (Hair et al., 2019). Prior to evaluating the structural model, the measurement model is assessed.

Application of the Proposed Methodology

Identification and Validation of Industry 4.0 Factors Using a Questionnaire-Based Survey

Design of the Questionnaire

A list of relevant questions for examining the relevance of identified factors of Industry 4.0 implementation was presented to the experts during the pilot study. This was done to review the layout of the questionnaire prepared based on

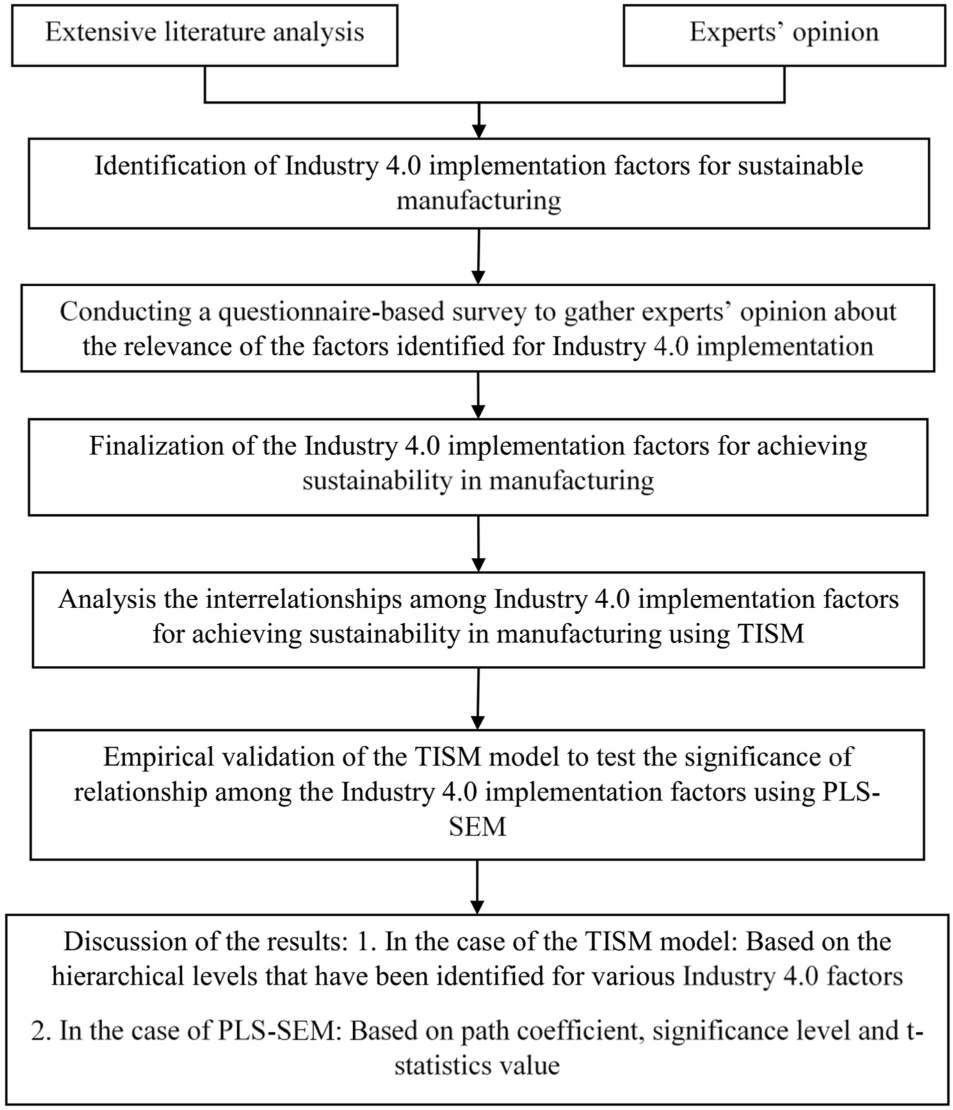

Fig. 1 Research flow and design adopted for present study

the literature review and examination of the research questions of this study. A pilot study was conducted with two academic researchers, three public-sector practitioners, and two private-sector practitioners to test the designed questionnaire. These experts were consulted in order to assess the questionnaire's correctness in terms of composition, readability, complexity, and completeness (Dillman, 1978). The content validity has been examined with the experts to test the language and understanding of the questionnaire. Finally, the questionnaire has been finalized based on the recommendations of the pilot study's experts. The questionnaire was divided into two sections, the first of which asked respondents to provide their basic demographic information, and the second of which asked them to provide their opinion or perception (on a Likert scale of 1-not critical to 5-very critical) on the factors influencing Industry 4.0 implementation for achieving sustainability in Indian manufacturing companies. In the pilot study, experts also emphasized the importance of defining the survey's target population or which companies should be involved in collecting survey responses. As a result, the ET 500 list and Indian Brand Equity Foundation list were explored to compile a list of potential respondents limited to the Indian manufacturing companies. The experts concluded that the factors given to them for evaluation were relevant to this study, and also, they did not suggest any additional Industry 4.0 factors. As a result, all measurement items (i.e., the 23 Industry 4.0 factors) were retained in their current form for gathering respondents' data from the considered different segments of the manufacturing sector.

Administration of the Questionnaire

The completed survey was circulated via e-mail to approximately 301 industrial practitioners, top-ranking officials of government departments, and academicians working in the area of intelligent manufacturing/Industry 4.0. The survey was also conducted offline (via a paper-based method) by meeting with the experts in person. The targeted companies were from different manufacturing domains like automobiles (OEMs and auto-component manufacturers), machine tools, electrical/electronic equipment, FMCG, process industry, etc. These organizations were chosen because they are utilizing Industry 4.0 technologies like IoT, big data analytics, cloud, simulation, robots, augmented reality, and 3D printing to drive their business operations. Initially, the response rate was very low. As a result, each non-respondent was reminded via e-mail, and these respondents were later followed up via phone calls, WhatsApp, personal visits, and re-mailings. Finally, 169 responses were received, with 146 of them being complete in every aspect, yielding a response rate of 48.50 percent. Since the response rate obtained is higher than that reported in the previous research by Devaraj et al. (2012), (e.g., 32.8 percent). As a result, the data gathered is adequate for further analysis. The demographic information of the respondents has been summarized as follows.

As per the respondents' profiles, there were 46 respondents from the public sector, 76 respondents from the private sector, and 24 respondents from the government and other organizations (including industry associations). In terms of educational qualifications, 100 respondents were graduates with a B.Tech or B.E degree, 34 were post-graduates with an M.E/M.TECH degree, and the remaining respondents had a doctoral degree in the related fields. Out of the overall respondents, 39 had less than 5 years of experience, 51 had 6 to 10 years of experience, 46 had 11 to 15 years of experience, and the remainder had more than 20 years of experience in the advanced technology implementation in the manufacturing sector. In terms of professional backgrounds, 46 respondents are from the automotive industry, 36 are from the electrical and electronic sector, 18 are from the fast-moving consumer goods (FMCG) industry, 27 are from the machine tool industry, and 19 are from the process industry.

Modeling the Interrelationships of Industry 4.0 Factors Using a Hierarchical Structural Model (TISM)

TISM Model Development

The following steps were taken into account while developing the TISM model:

Step A Identification of Industry 4.0 factors for achieving sustainability

A thorough assessment of the literature and expert feedback gathered through a questionnaire were used to identify the factors. Table 1 shows the list of twenty-three factors chosen for the study.

Step B Determination of the contextual relationship

The contextual relationship between the two variables must be defined before developing a hierarchical structural model. The contextual relationship between two variables can be described as follows: The contextual relationship between two factors can be stated as: 'Factor 1 will affect Factor 2.' The same experts who rated the importance of factors identified through literature were consulted to determine the contextual relationship between these factors.

Step C Interpretation of contextual relationship

ISM depicts the interrelationships between variables clearly, but it does not explain why these interrelationships exist. An interpretation of the factor's contextual relationship is needed to gain an understanding of the explanation for these interrelationships. This step distinguishes ISM from the TISM approach in that it provides complete information on the existence of relationships. By interpretation, we mean 'how factor 1 would influence factor 2.'

Step D Interpretive logic-knowledge base for pairwise comparison

In ISM, a pairwise comparison of two variables results in the formation of a self-structured interaction matrix (SSIM). TISM, on the other hand, develops an interpretive logic-knowledge base to reflect the pairwise contrast of the variables. The authors distributed the questionnaire to the experts and asked them to respond with a Yes or No for the contextual relationship between two variables. Additionally, they were asked to state the explanation for their answer (if Yes) regarding the contextual relationship between the two variables so that an interpretive logic-knowledge base could be prepared. After gathering responses from all experts, the relationships (statements) that were labeled as Yes by experts (more than 70% of the total) were considered valid in this analysis.

Step E Constructing the initial reachability matrix (IRM)

The IRM was developed by translating the '*Y*' and '*N*' symbols in the interpretive logic-knowledge base into binary digits (i.e., '1' and '0'). Table 2 shows the IRM that was developed for the TISM model.

Step F Constructing the final reachability matrix (FRM)

By applying the transitivity rule to the initial reachability matrix, the FRM was developed. In accordance with the transitivity rule, if factor X is associated with factor Y and factor Y is associated with factor Z, then factor X is also transitively associated with factor Z. In FRM, the "$*$" symbol denotes the transitivity among the variables. The interpretive logic-knowledge base must be updated in order for there to be a transitive relation

Table 2 Initial reachability matrix for Industry 4.0 implementation factors

	FI	F2	F3	F4	F5	F6	F7	F8	F9	F10	Fll	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23
Fl	1	1	1	0	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	I	0	0
F2	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
F3	0	0	1	0	0	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0
F4	0	0	0	1	0	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F5	0	1	0	0	1	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
F6	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	0	1	1	0	0
F7	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
F8	0	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
F9	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	0	1	0	0	0	0	0
F10	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1
Fll	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
F12	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0
F14	0	0	1	1	0	1	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0
F15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
F16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
F17	0	1	1	1	0	1	0	0	1	0	0	1	0	1	0	0	1	0	1	1	1	0	1
F18	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0
F19	0	0	1	0	0	0	0	1	1	0	0	1	0	1	0	0	0	0	1	0	0	0	0
F20	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	1	1	0	0
F21	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0
F22	0	1	1	0	0	1	1	1	1	0	0	1	0	0	0	0	0	0	1	0	1	1	0
F23	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1

between the two variables. If there is a transitive relation, the entry should be modified by specifying yes instead of no, and the word 'transitive' should be written in the interpretation column of a knowledge base. Table 3 shows the final reachability matrix developed for Industry 4.0 factors.

Step G Performing level partitioning

The level partitioning has been performed to assign all the variables to hierarchical levels and to indicate the antecedent and reachability set for each factor. For each factor, reachability and antecedent set has been derived from the final reachability matrix. In addition, the intersection set was derived from the intersection of the respective reachability and the antecedent set. If a factor's intersection set and reachability set are the same, then that factor is at the top of the TISM hierarchy (or Level 1). The variable at the top of the hierarchy is omitted entirely for the next iteration, and this is repeated for each iteration until each element in the hierarchy reaches its level. Table 4 shows that the factor (i.e., customer satisfaction (F15)) is at level 1 in the TISM hierarchy. In level 2, factors such as sustainability through controlled consumption (F16), flexibility and mass customized production (F18), and lean production through lead time reduction (F13) were obtained. Thirteen levels were obtained after thirteen iterations, as shown in Table 4.

Step H Development of Interpretive matrix

The binary interaction matrix was developed using the digraph by converting all interactions associated with direct links and significant transitive links to "1." "0" is used for indirect and no-connection links. This binary interaction matrix was then upgraded with the interpretive logic-knowledge base to develop the interpretive matrix. The details of the interpretive logic-knowledge base used to develop the interpretive matrix are shown in Appendix.

Step I Framing total interpretive structural model

The TISM model was developed by combining the details from the interpretative matrix and the digraph. The interpretations obtained from the interpretive matrix can be seen along the side of the respective links in the TISM diagram. However, instead of highlighting the interpretation in the TISM diagram, these are outlined in Appendix 1 to make the explanation clearer. In the TISM

Table 3 Final reachability matrix for Industry 4.0 implementation factors

	Fl	F2	F3	F4	F5	F6	F7	FS	F9	F10	Fll	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23
Fl	1	1	1	1*	0	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	1	0	1*
F2	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1*
F3	0	0	1	1*	0	1	1	1	1	1	1	1	1*	1	1*	1*	0	1*	0	1*	0	0	1*
F4	0	0	0	1	0	1	0	1	1	1	1	0	1*	0	1*	1*	0	1*	0	1*	0	0	0
F5	0	1	1*	1*	1	1*	1	1*	1	1*	1*	1*	1*	1*	1	1	1*	1*	1*	1*	0	0	1*
F6	0	0	0	0	0	1	1*	0	1*	0	1	0	1	0	1*	1	0	0	0	1	1	0	0
F7	0	0	0	0	0	0	1	0	1	0	1	0	0	0	1*	1*	0	1*	0	0	0	0	0
F8	0	0	0	1	0	1	1*	1	1	1*	1*	0	0	0	1*	1*	0	1*	0	1*	1	0	0
F9	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	0	1	0	0	0	0	0
F10	0	0	0	0	0	1	1*	0	1	1	1	0	0	0	1*	1*	0	1*	0	1*	0	0	1
Fll	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1*	1*	0	1*	0	0	0	0	0
F12	0	0	1	1*	0	1*	1*	1	1*	1*	1*	1	0	1*	1*	1*	0	1*	0	1*	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1*	0	1	0	0	0	0	0
F14	0	0	1	1	0	1	1*	1*	1	1	1	1*	0	1	1*	1*	0	1*	0	1*	0	0	1*
F15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
F16	0	0	0	0	0	0	0	0	0	0	0	0	1*	0	1	1	0	1	0	0	0	0	0
F17	0	1	1	1	0	1	1*	1*	1	1*	1*	1	1*	1	1*	1*	1	1*	1	1	1	0	1
F18	0	0	0	0	0	0		0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0
F19	0	0	1	1*	0	1*	1*	1	1	1*	1*	1	1*	1	1*	1*	0	1*	1	1*	0	0	0
F20	0	0	0	0	0	0	1	0	1	0	1	0	1*	0	1*	1*	0	1*	0	1	1	0	0
F21	0	0	0	0	0	0	1	0	1	0	1*	0	1*	0	1*	1*	0	1*	0	1	1	0	0
F22	0	1	1	1*	0	1	1	1	1	1*	1*	1	1*	0	1*	1*	1*	1*	1	1*	1	1	0
F23	0	0	0	0	0	1	1*	0	1	1	1	0	1*	0	1*	1*	0	1*	0	1*	0	0	1

model, dotted and solid lines denote significant transitive and main links, respectively.

Validation of the Interrelationships of Industry 4.0 Factors Established by the TISM Model Using PLS-SEM

Obtaining the Underlying Constructs Among the Finalized Industry 4.0 Factors Using Exploratory Factor Analysis (EFA)

Using SPSS version 23, EFA was used to determine underlying constructs among the twenty-three Industry 4.0 factors. Principal component analysis with orthogonal varimax rotation has been used to obtain the constructs. Before using the EFA, the questionnaire dataset's reliability and non-response bias were examined using a variety of statistical tests, as discussed below:

Non-response bias may exist in the data gathered online. As a result, the t-test was used to evaluate the biased answers, which were divided into two categories depending on the time at which respondents answered the questionnaire (i.e., early and late) (Armstrong and Overton 1977; Shibin et al., 2018). At the 0.05 significance range, the t-test results revealed that there is no significant difference between the mean values of early and late respondents' responses (Luthra & Mangla, 2018). Similar approach has been followed by Wamba and Queiroz (2022) to test the non-response concern. Cronbach's alpha was computed to confirm the reliability of the responses, and a value of 0.945 was obtained for the dataset obtained through a questionnaire survey. This implies that the responses have a high level of internal accuracy. Furthermore, the EFA dataset's suitability is determined by evaluating the two key parameters (Marzouk & Elkadi, 2016). These parameters include the inter-correlation strength among items and sample adequacy, which was checked using three main metrics (i.e., (i) matrix correlation check, (ii) Kaiser–Meyer–Olken (KMO) sampling adequacy measure, and (iii) Bartlett's test of sphericity). According to Al-Gahtani et al. (2016), if the correlation between variables is less than 0.3, the dataset is inappropriate for EFA. The KMO value varies from 0 to 1, with a value greater than 0.70 being preferred. However, the KMO measure of 0.876 in the present study indicates that the

Table 4 A summary of all iterations related to FRM level partitioning

Factors	Reachability set	Antecedent set	Intersection set	Level
F1	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23	1	1	XIII
F2	2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23	1, 2, 5, 17, 22	2	XII
F3	3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 18, 20, 23	1, 2, 3, 5, 12, 14, 17, 19, 22	3	X
F4	4, 6, 8, 9, 10, 11, 13, 15, 16, 18, 20	1, 2, 3, 4, 5, 8, 12, 14, 17, 19, 22	4	IX
F5	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 23	5	5	XIII
F6	6, 7, 9, 11, 13, 15, 16, 20, 21	1, 2, 3, 4, 5, 6, 8, 10, 12, 14, 17, 19, 22, 23	6	VII
F7	7, 9, 11, 15, 16, 18	1, 2, 3, 5, 6, 7, 8, 10, 12, 14, 17, 19, 20, 21, 22, 23	7	V
F8	4, 6, 7, 8, 9, 10, 11, 15, 16, 18, 20, 21	1, 2, 3, 4, 5, 8, 12, 14, 17, 19, 22	8	IX
F9	9, 13, 15, 16, 18	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 17, 19, 20, 21, 22, 23	9	III
F10	6, 7, 9, 10, 11, 15, 16, 18, 20, 23	1, 2, 3, 4, 5, 8, 10, 12, 14, 17, 19, 22, 23	10	VIII
F11	9, 11, 15, 16, 18	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 14, 17, 19, 20, 21, 22, 23	11	IV
F12	3, 4, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 18, 20	1, 2, 3, 5, 12, 14, 17, 19, 22	12	X
F13	13, 15, 16, 18	1, 2, 3, 4, 5, 6, 9, 13, 16, 17, 18, 19, 20, 21, 22, 23	13	II
F14	3, 4, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 18, 20, 23	1, 2, 3, 5, 12, 14, 17, 19	14	X
F15	15	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	15	I
F16	13, 15, 16, 18	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16, 17, 18, 19, 20, 21, 22, 23	16	II
F17	2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23	1, 2, 5, 17, 22	17	XII
F18	13, 15, 16, 18	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14, 16, 17, 18, 19, 20, 21, 22, 23	18	II
F19	3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 18, 19, 20	1, 2, 5, 17, 19, 22	19	XI
F20	7, 9, 11, 13, 15, 16, 18, 20, 21	1, 2, 3, 4, 5, 6, 8, 10, 12, 14, 17, 19, 20, 21, 22, 23	20	VI
F21	7, 9, 11, 13, 15, 16, 18, 20, 21	1, 2, 6, 8, 17, 20, 21, 22	21	VI
F22	2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21, 22	22	22	XIII
F23	6, 7, 9, 10, 11, 13, 15, 16, 18, 20, 23	1, 2, 3, 5, 10, 14, 17, 23	23	VIII

dataset is appropriate for EFA and that factors can be extracted easily. The Bartlett test of sphericity was used to test the null hypothesis that the correlation matrix is an identity matrix. For this research, Bartlett's measure with a significance value of 0.000 (p-value < 0.05) and a Chi-square value of 2652.923 demonstrates that the correlation matrix is not an identity matrix and, therefore, the dataset is suitable for EFA. According to Chen and Kuo (2017), a factor loading value greater than 0.50 is preferable for loading a factor on a given construct. The EFA results show that all 23 items have a factor loading value greater than 0.50. Finally, the 23 items were loaded and extracted into five constructs with an eigenvalue greater than 1.0. Furthermore, because data on Industry 4.0 factors were collected from a single group of participants at a specific point in time, there may be a problem with common method bias (CMB), which occurs when one general factor accounts for the majority of covariance. As a result, Harman's single-factor approach (Harman, 1967; Podsakoff & Organ, 1986) was used during EFA to analyze this problem. The findings revealed that the first factor accounted for 24.708 percent of the total variance, indicating that no CMB issues exist.

Endogeneity appears to be a problem similar to CMB, and it may arise from a common source and common-method variance (Antonakis et al., 2010). The issue of endogeneity is linked to data obtained through survey and secondary sources, according to Antonakis et al. (2010) and Reeb et al. (2012). This error can be minimized by avoiding common-method variance and using techniques like Harman's single factor test, market-variable approach, and confirmative factor analysis approach (Deng et al., 2016). All factors accounted for 69.532 percent of the total variance in the data for this study, indicating that common method biases would not have an effect on our data analysis. This also means that there is no endogeneity in this study. Table 5 shows the results of the exploratory factor analysis.

Evaluation of Measurement Model

Hair et al. (2019) outlined four steps for evaluating the measurement model in relation to the specific research area. They are as follows: (a) indicator loading determination, (b) determination of internal consistency reliability, (c) determination of convergent validity, and (d) determination of discriminant validity. Some key essential indicators must be checked for each step of evaluation. For e.g., according to Falk and Miller (1992), the loading factor value for each item should be greater than 0.5. Table 6 reveals that all of the item loadings are greater than 0.5, indicating that the items are suitable in terms of individual reliability. The three most common criteria for measuring the internal consistency reliability are as follows: (a) Cronbach's alpha, (b) Dijkstra–Henseler's rho (ρA), and (c) composite reliability. Many researchers have defined the acceptable limit for each measure's validity, such as Cronbach's alpha (value should be greater than 0.7), Dijkstra–Henseler's rho (value should be greater than 0.7), and composite reliability (value should be more than 0.7). The next criterion to consider is convergent validity, which can be examined using the average variance extracted (AVE) measure. To justify the construct's convergent validity, the value of AVE should be greater than or equal to 0.5 (Fornell & Larcker, 1981). Finally, the discriminant validity of the parameter can be examined by comparing the square root of the AVE (diagonal values) with the correlation among the latent variables. The square roots of AVEs must be greater than their corresponding correlation coefficients to ensure discriminant validity. The diagonal elements in Table 7 were greater than the correlation coefficients in the same row, indicating discriminant validity. Table 6 shows the measurement model's results, and it can be seen that all of the measures obtained values that were within the acceptable range. This clearly indicates that the measurement model is accurate and valid.

Table 5 Results of exploratory factor analysis (EFA)

Item	Rotated component matrix					Construct name
	1	2	3	4	5	
F5	0.631					Social and environmental-related factors (SERF)
F8	0.739					
F20	0.667					
F21	0.585					
F22	0.733					
F23	0.774					
F7		0.557				Organizational related factors (ORF)
F9		0.849				
F11		0.587				
F12		0.518				
F19		0.679				
F4			0.521			Technological related factors (TRF)
F6			0.782			
F10			0.754			
F14			0.666			
F1				0.531		Strategic related factors (SRF)
F2				0.791		
F3				0.707		
F17				0.615		
F13					0.522	Performance-related factors (PRF)
F15					0.741	
F16					0.560	
F18					0.659	

Table 6 Statistics results of the measurement model (loadings, Cronbach's alpha (α), Dijkstra–Henseler's rho (ρA), composite reliability (CR), and average variance extracted (AVE)

Construct	Item	Outer weights/Loadings	α	ρA	CR	AVE
Organizational related factors (ORF)	F7	0.769	0.810	0.817	0.869	0.570
	F9	0.702				
	F11	0.828				
	F12	0.779				
	F19	0.690				
Performance-related factors (PRF)	F13	0.763	0.750	0.754	0.841	0.569
	F15	0.739				
	F16	0.786				
	F18	0.728				
Social and environment -related factors (SERF)	F5	0.855	0.880	0.895	0.909	0.626
	F8	0.840				
	F20	0.803				
	F21	0.688				
	F22	0.767				
	F23	0.783				
Strategic related factors (SRF)	F1	0.810	0.828	0.828	0.887	0.666
	F2	0.877				
	F3	0.881				
	F17	0.680				
Technological related factors (TRF)	F4	0.829	0.824	0.835	0.884	0.658
	F6	0.848				
	F10	0.676				
	F14	0.878				

Table 7 Fornell–Larcker Criterion analysis for examining discriminant validity

Construct	Organizational related factors (ORF)	Performance-related factors (PRF)	Social and environment-related factors (SERF)	Strategic related factors (SRF)	Technological related factors (TRF)
Organizational related factors (ORF)	0.755				
Performance-related factors (PRF)	0.745	0.755			
Social and environment-related factors (SERF)	0.679	0.619	0.791		
Strategic related factors (SRF)	0.745	0.718	0.741	0.816	
Technological related factors (TRF)	0.621	0.732	0.670	0.710	0.811

Assessment of Structural Model

After obtaining satisfactory statistical results for the measurement model, the next step in the PLS-SEM methodology is structural model assessment (Hair et al., 2019). While analyzing the structural model, certain parameters need to be investigated. These are (a) the coefficient of determination (R^2), (b) the blindfolding-based cross-validated redundancy measure/predictive relevance (Q^2), (c) path coefficient (β) and their significant level, and (d) f^2

(effect size) for obtaining the substantial impact of the exogenous variable on an endogenous variable (Hair et al., 2014). The acceptable range and significance of each parameter have been discussed as follows:

(a) *Coefficient of determination (R^2)* It is a metric for determining the model's explanatory power that evaluates the explained variance for each dependent construct. According to Hair et al. (2011), constructs with R^2 values of 0.75, 0.50, and 0.25 will reflect significant, moderate, and poor model exploratory power, respectively. The following R^2 values were obtained for four dependent constructs: 0.588 for SERF, 0.681 for PRF, 0.555 for ORF, and 0.524 for TRF, all of which indicate that the model's exploratory power is satisfactory.

(b) *Path coefficient (β)* This is an important metric for assessing the significance of relationships between endogenous and exogenous variables. To obtain β and their related *t*-values, a PLS bootstrapping procedure with a resample size of 5000 should be used. β will have a value ranging from 0 to 1. In order to measure the significance of various relationships, the study used a 5% significance level for the critical value. If the empirical t-value is greater than the critical *t*-value, the hypothesis is agreed at this level of significance (Agrawal & Singh, 2019). The β values obtained for the present study are indicated in Table 8.

(c) *Predictive relevance (Q^2)/blindfolding-based cross-validated redundancy measure* It is regarded as an important criterion for determining the predictive accuracy of the PLS path model. For the reflective measurements model, the blindfolding procedure is used to obtain the Q^2 value (Hair et al., 2014). This procedure aims to exclude all data points from the endogenous construct's indicators before estimating the model's parameter using the remaining data points (Henseler et al., 2009). As a general rule, Q^2 values greater than 0, 0.25, and 0.50 denote minimal, medium, and significant predictive relevance, respectively (Hair et al., 2019). Furthermore, the relative influence of predictive relevance can be calculated in terms of size effect q^2, which is similar to the effect size f^2. The q^2 values of 0.02, 0.15, and 0.35, respectively, reflect the small, medium, and strong effects of the exogenous latent variable on the given endogenous variable (Agrawal & Singh, 2019). The Q^2 values for all constructs were found to be positive in this study, with values obtained as follows: 0.357 for ORF construct, 0.283 for PRF construct, 0.473 for SERF construct, 0.445 for SRF construct, and 0.433 for TRF construct. This also means that the developed model is overall consistent and suitable. Table 8 shows the results of the structural model assessment.

The results reveal that SRFs significantly and positively affect ORFs ($\beta = 0.745$, *p*-value < 0.05), SERFs ($\beta = 0.503$, *p*-value < 0.05), TRFs ($\beta = 0.556$, *p*-value < 0.05), and PRFs ($\beta = 0.158$, *p*-value < 0.05). The findings also reveal that, ORFs positively affect SERFs ($\beta = 0.253$, *p*-value < 0.05), TRFs ($\beta = 0.208$, *p*-value < 0.05) and PRFs ($\beta = 0.395$, *p*-value < 0.05). The findings also reflect significant and positive relationship between the remaining hypothesized relationships i.e., ($\beta = 0.374$, *p*-value < 0.05) for TRFs & PRFs and ($\beta = 0.069$, *p*-value < 0.05) for PRFs & SERFs.

Discussion of the Results

The present study makes an attempt to develop a detailed understanding of the interrelationships among various factors of Industry 4.0 implementation for achieving sustainability in manufacturing organizations, with a focus on emerging economies such as India. To accomplish this,

Table 8 Structural model path coefficients (β), *t*-statistics and *p*-values

Relationship	β	*t*-Statistics	*p*-values
SRF positively effect ORF	0.745	16.381	0.000
SRF positively effect TRF	0.556	7.718	0.000
SRF positively effect PRF	0.158	1.376	0.000
SRF positively effect SERF	0.503	5.214	0.000
ORF positively effect TRF	0.208	2.477	0.013
ORF positively effect PRF	0.395	3.518	0.000
ORF positively effect SERF	0.253	2.337	0.020
TRF positively effect PRF	0.374	2.730	0.006
PRF positively effect SERF	0.069	0.768	0.000

twenty-three Industry 4.0 implementation factors were identified through extensive literature review and validated using a questionnaire-based survey. Second, the TISM methodology has been used to develop a hierarchical structure model to recognize the interrelationships between the implementation factors. Finally, the statistical significance of these interrelationships between the main constructs of factors was tested and validated using PLS-SEM.

The study's findings revealed that the developed TISM model has been partitioned into thirteen levels (see Fig. 2). The first level in the hierarchical structural model was occupied by factors such as continuous support and commitment from top management (F1), adequate labor laws for less-skilled workforce working in the digital environment (F22), and environmental regulations for sustainability (F5). This means that these factors are strategically essential for the successful implementation of Industry 4.0.

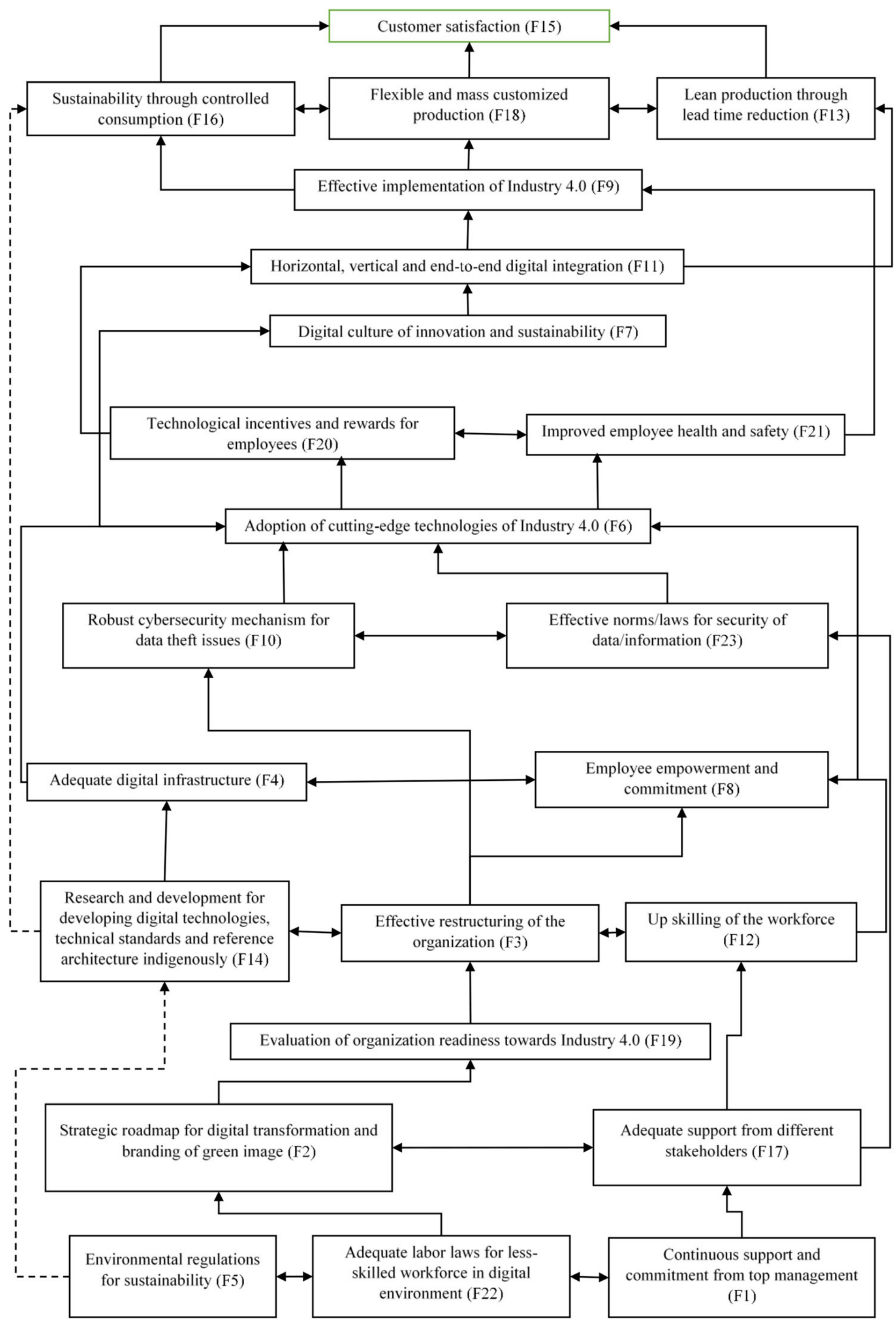

Fig. 2 TISM model for Industry 4.0 implementation factors

Various scholars have discussed the significance of these factors in past studies. Ghobakhloo (2018), for example, reported that a determined leadership style from top management is required to develop short, medium, and long-term plans while implementing Industry 4.0. As is well known, the Industry 4.0 concept would necessitate extensive reorganization of the organization's existing infrastructure, which would undoubtedly rely on senior management's clear vision and strong commitment (de Sousa Jabbour et al., 2018). According to Devi et al. (2021), top management role and assistance is critical for Industry 4.0 because they are solely accountable for formulating and implementing a well-defined strategic roadmap toward Industry 4.0. On the one side, recent technological advancements such as Industry 4.0 and smart manufacturing are intended to bring different socioeconomic and environmental benefits to the organization. The societal benefits of Industry 4.0 include increased employee health and safety, a better working environment for employees, and effective human–machine collaboration (Herrmann et al., 2014). The emergence of innovative business models as a result of Industry 4.0 implementation would enhance the profitability and production performance of industrial enterprises (Kumar et al., 2022). On the other side, the digital innovations of Industry 4.0 may necessitate higher resource use and high energy requirements to function appropriately (Tseng et al., 2018). Adoption of environmental legislation is therefore critical in this context. Furthermore, appropriate regulatory protections for low-educated jobs must be introduced in order to ensure social sustainability by preserving their position in the Industry 4.0 era. Krishnan et al. (2021) also emphasize the importance of developing and implementing labor and safety laws while operating in a digitally enabled environment such as Industry 4.0.

Level II of the TISM hierarchy includes adequate support from different stakeholders (F17) as well as a strategic roadmap for digital transformation and branding of green image (F2). The joint engagement of various stakeholders from government organizations, academic institutions, research centers, and business companies can effectively accomplish the implementation objectives of Industry 4.0. The main requirements for implementing Industry 4.0 include an advanced IT infrastructure, appropriate training for digital skills, innovative research and development practices, and applicable labor regulations and data theft management legislation. According to Erol et al. (2016), inadequate financial support is a significant impediment to the implementation of Industry 4.0 among small- and medium-sized enterprises (SMEs). Therefore, sufficient budgetary support from multiple stakeholders is needed to fulfill the requirements of Industry 4.0. According to the majority of scholars' (Kumar et al., 2021; Moktadir et al., 2018; Osterrieder et al., 2020) studies, organizations lack a defined strategy, vision, and roadmap for implementing Industry 4.0. Establishing adequate and clear strategic guidelines for the major requirements of Industry 4.0 is important for its effective implementation. Assessments of information technology (IT) governance, digital marketing maturity, and digital capabilities within the workforce are just a few examples (Ghobakhloo, 2018). Butt (2020) emphasized the necessity of a well-defined strategic roadmap for Industry 4.0 as a crucial mechanism for organizing the necessary arrangements within the organization for a smooth transition and the achievement of significant benefits through embracing digital technologies.

Level III of the TISM hierarchy is the evaluation of an organization's readiness toward Industry 4.0 (F19). According to Hanafiah et al. (2020), recognizing the most important aspects of Industry 4.0 readiness is key for establishing self-assessment models to evaluate an organization's preparedness for Industry 4.0. One of the well-recognized readiness models is "IMPULS-Industrie 4.0 Readiness" (Sony & Naik, 2020a). Therefore, the selection of a suitable readiness model would enable the practitioners to identify their organization's current capabilities in the context of Industry 4.0, based on their enabling environment.

The fourth level of the TISM consists of three factors: effective restructuring of the organization (F3), upskilling of the workforce (F12) and research and development for developing technologies indigenously, technical standards, and reference architecture (F14). As Industry 4.0 implementation is characterized by the digital integration of Information Technologies (IT) and Operational Technologies (OT), it is expected that Industry 4.0 will necessitate a significant shift in the existing business model (Zorrilla & Yebenes, 2022). As a result, practitioners should pay close attention to the organization's existing resources (e.g., workforce, processes, and technology) when restructuring the organization in accordance with Industry 4.0 (Kumar et al., 2021). The workforce would need advanced soft and hard skills in the future manufacturing systems (Horváth & Szabó, 2019), so that new employment responsibilities could be handled efficiently. Workers with low levels of education would be socially impacted by Industry 4.0. As a result, reskilling and upskilling employees (Agarwal et al., 2021) is necessary to enhance existing employees' digital competencies by adopting appropriate training and learning programs. Adequate skills and digital capabilities are critical metrics that top management must effectively strengthen to achieve success while transitioning to Industry 4.0. The organizations need to invest in research and development (R&D) for indigenously developing cutting-edge technologies of Industry 4.0 and their technological requirements, i.e., standards for seamless

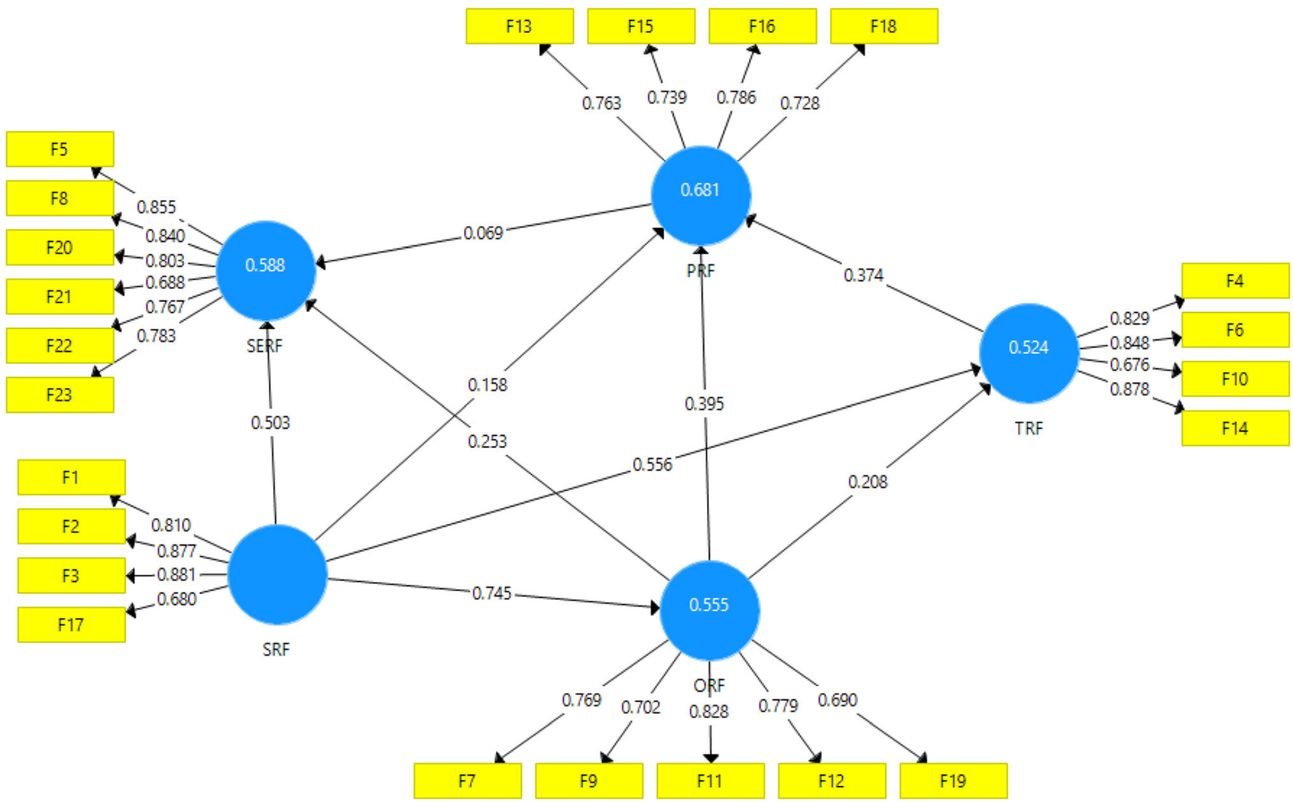

Fig. 3 Structural model with path coefficient (β), adjusted R^2 values, and outer loading values

integration of various entities in the smart factory. The academic and research institutions are seen as vital in promoting a culture of research, learning, and innovation in light of recent technological trends such as Industry 4.0 (AIMA-KPMG Report, 2018).

The level V of the TISM hierarchy was occupied by adequate digital infrastructure (F4) and employee empowerment and commitment (F8). Kamble et al. (2020) stated that digital infrastructure would be the primary requirement of Industry 4.0 for achieving end-to-end digital integration across all entities in the smart factory. Industry 4.0 would offer social benefits such as employee welfare, better communication, employee empowerment (Yilmaz et al., 2021). These benefits would boost employee morale due to increased autonomy and the responsibility to be innovative in complex decision-making situations. Level VI of the TISM hierarchy includes two factors: robust cybersecurity mechanism for data theft issues (F10) and effective regulations/norms for the security of data/information (F23). Cybersecurity and data protection concerns would be significant impediments to Industry 4.0 implementation (Sung, 2018). Thus, adopting appropriate cybersecurity mechanisms such as encryption, the latest software updates, and vulnerability scanning would prevent unauthorized access to information/data while simultaneously lowering the risk of data theft (Lezzi et al., 2018). Furthermore, legal regulations/laws would be needed to protect the data's confidentiality, copyrights, intellectual property rights (IPR), reliability, and authenticity when it is shared privately (Schröder, 2016). Adequate regulation would thereby ensure the long-term sustainability of the organization's digital networks.

Adoption of digital technologies of Industry 4.0 (F6) is the seventh level in the TISM hierarchy. Adopting emerging technologies is viewed as a strategic measure in today's global business environment to maintain a competitive advantage. According to Dalenogare et al. (2018), digital connectivity through the adoption of Industry 4.0 technologies will assist businesses in improving their industrial efficiency.

Level VIII of the TISM hierarchy includes technological incentives and rewards to employees (F20) and improved employee health and safety (F21). The employees must be encouraged and motivated to support digitalization efforts by providing technological incentives (Lin et al., 2018). Industry 4.0 would also improve the social dimension of sustainability by improving employee health and safety, providing a better working environment with less physical stress to employees, and offering flexibility in work (Bai et al., 2020; Müller et al., 2018). This would result in increased employee satisfaction and motivation.

Level IX of the TISM hierarchy consists of a digital culture of innovation and sustainability (F7). Lack of digital culture and training is an internal organizational concern that is much more severe than external concerns such as required digital infrastructure, appropriate technical standards, cybersecurity, intellectual property rights, and data privacy concerns (Lee et al., 2017). Horizontal, vertical, and end-to-end digital integration (F11) constitutes Level X of the TISM hierarchy. The comprehensive digital integration across the smart manufacturing ecosystem will transform how products are manufactured and delivered in existing manufacturing systems (Hofmann & Rüsch, 2017). Effective implementation of Industry 4.0 (F9) occurred at level XI of the TISM hierarchy. According to Vaidya et al. (2018), adopting digitalization themes such as Industry 4.0 has become a critical requirement for modern industrial organizations.

Level XII of the TISM hierarchy includes lean production through lead time reduction (F13), flexible and mass customized production (F18), and sustainability through controlled consumption (F16). These (F13, F18, and F16) are an organization's main capabilities that can give them a competitive advantage once Industry 4.0 is successfully implemented. According to Bai et al. (2020), technological advancements of Industry 4.0 are beneficial to organizations in successfully managing their operational activities, allowing them to obtain benefits toward sustainable development goals (SDGs), which in turn enhances their legitimacy status. Customer satisfaction (F15) is at the top of the TISM hierarchy. Industry 4.0 has the unique ability to enhance customer satisfaction based on precise information and data obtained on customer demand trends such as design requirements, quality, orders, and scheduling (Chiarini et al., 2020; Foidl & Felderer, 2015). Furthermore, Kiraz et al. (2020) highlighted that implementing Industry 4.0 would improve the organization's competitive image by increasing market shares and enhancing present customer satisfaction. Due to the highest dependence of this factor (i.e., customer satisfaction, F15) on other factors of Industry 4.0 implementation, it has been obtained in the top level hierarchy of the TISM model.

Furthermore, this paper addresses the proposed TISM model's limitation by providing empirical evidence for the presence of interrelationships using the PLS-SEM methodology. The research hypotheses were examined to evaluate the structural model, and a bootstrapping procedure was used to extract the values of path coefficients and object loadings from 200 cases and 5000 random samplings (Chin, 1998). The findings show that, at a significance level of 0.001, all hypothesized relationships for different constructs of Industry 4.0 implementation factors were positive and significant (see Table 8). Figure 3 shows the final structural model developed with the SmartPLS3 software (Ringle et al., 2015). All of the required metrics for both measurement and structural model were tested, and the findings show that they were all within the acceptable range, as defined by different researchers in previous literature studies (Hair et al., 2014).

The PLS-SEM analysis confirmed that strategic related factors (SRFs) influence organizational related factors (ORFs), technological related factors (TRFs), social and environmental-related factors (SERFs), and performance-related factors (PRFs) in the context of Industry 4.0 implementation. This means that SRFs are the primary determinants of Industry 4.0 implementation for achieving sustainability in manufacturing. This construct has four sub-criteria factors (F1, F2, F3, and F17) that drive the rest of the factors in the remaining constructs. Tables 6, 7 and 8 summarize the results of the PLS-SEM analysis used to evaluate measurement and structural models for Industry 4.0 factors. These findings showed that the TISM model is statistically fit and empirically justified for depicting the relationships between the Industry 4.0 implementation factors for sustainable manufacturing.

Theoretical Implications

Few studies have looked into Industry 4.0 implementation factors for achieving sustainability, and even fewer have looked into the interrelationship between Industry 4.0 implementation factors and sustainability. There is no study that models and validates the mutual interrelationships among Industry 4.0 implementation criteria for sustainable manufacturing in the Indian context in the literature. As a result, utilizing a hybrid TISM and PLS-SEM approach, this research makes a unique contribution by identifying and modeling factors affecting the implementation of Industry 4.0 for sustainable manufacturing in Indian manufacturing organizations.

Managerial Implications

The present research provides a clear and detailed understanding of the exact nature of factors through the development of a hierarchical structural model and its validation in order to better manage the Industry 4.0 implementation for sustainability. The proposed TISM model depicts the interrelationships among Industry 4.0 factors, assisting practitioners in identifying the most important implementation factors for Industry 4.0 based on their driving and dependent nature. Accurate information/knowledge about the factors would aid stakeholders in developing a detailed strategic plan for the transformation from traditional manufacturing setup to Industry 4.0.

According to the TISM model, the top three critical factors for implementing Industry 4.0 are F5, F22, and F1, since these factors represent high driving and low dependence on the rest of the factors. The results of this study indicate that factors such as F5, F22, and F1 have a maximum influence on Industry 4.0 implementation, which is emphasized by past literature studies on Industry 4.0 (Krishnan et al., 2021; Shamim et al., 2016; Sony & Naik, 2020b), and practitioners must make every attempt to manage these factors. As a result, policymakers are recommended to formulate and effectively enforce environmental regulations and labor laws for the less-educated workforce engaged in a digital environment. Furthermore, the manufacturer must ensure that its top managers are focused and determined while making managerial decisions to restructure the organization in accordance with Industry 4.0 (Kumar et al., 2021). These factors should be given special consideration because they are independent of others but have a significant impact on implementation. The hypothesis relationship derived for different constructs based on PLS-SEM also offers valuable insights to top management about the relative significance of interrelationship between the independent and dependent factors. The awareness of the relative importance of factors would assist managers in focusing on the relevant factors, enabling resources and actions to be prioritized appropriately in the right direction. The paper's findings indicate that manufacturing organizations willing to adopt Industry 4.0 technologies would gain a competitive advantage as well as significant social and environmental benefits.

Conclusions

An integrated TISM and PLS-SEM approach was used in this paper to identify, model, and validate factors relevant to Industry 4.0 implementation for sustainable manufacturing. To achieve the paper's objectives, the TISM was first used to depict the interrelationship between the factors. Following that, the TISM-identified relationships were examined by analyzing various hypotheses, and the nature of the factor relationships and their significance on Industry 4.0 implementation were determined using a PLS-SEM. The TISM model segmented the twenty-three factors into thirteen levels. Factors such as F1, F5, and F22 were found at the bottom of the TISM hierarchy. F15 was at the top of the TISM hierarchy, while factors such as F13, F16, and F18 also have higher degree of dependency and were placed below it. The factors (i.e., F1, F5, and F22) at the bottom of the TISM hierarchy are strategic in nature and of critical importance due to their strong driving characteristics. These strategic factors have complete control over the dependent factors (existing at a higher level). As a result, these lower-level factors in TISM hierarchy are critical for stakeholders making strategic decisions about Industry 4.0 implementation in order to achieve manufacturing sustainability. The PLS-SEM findings revealed that all hypothesized relationships between each construct of Industry 4.0 were positive and significant, with the strategic related factors (SRF) construct having the greatest influence on implementation when compared to other constructs of Industry 4.0 factors. The remaining hypothesized relationships were found to have a low to moderate influence on Industry 4.0 implementation.

Limitations and Scope for Future Work

The present study provides valuable insights to practitioners of manufacturing organizations. However, it has some drawbacks. In the present study, only twenty-three factors were considered. However, more factors could be identified and analyzed in future studies. The study uses an integrated TISM and PLS-SEM approach to analyze the implementation factors of Industry 4.0 while taking into account the Indian manufacturing organization. The TISM model can be modified to other emerging economies with minor changes in the future. Furthermore, in the future, MICMAC analysis can be combined with the TISM model to determine the interdependence and driving power of the factors under consideration. The single-factor Harman's test was utilized to rule out common method bias (CMB) issues in this study. Other tests, such as the Markers Test, could be utilized in the future.

Since Industry 4.0 is still in its early phases of implementation, practitioners' assessments of its implications are still unclear. As a result, the current study was able to obtain questionnaire survey responses from 146 participants from manufacturing organizations. However, as the concept matures and gains clarity in practitioners' minds in the coming years, a larger sample size for performing the analysis on identified factors may be considered in the future.

Appendix

The following table contains the details of the interpretive logic-knowledge base that was used to construct the interpretive matrix:

Bilateral relationships between the factors	Reasons for the existence of relationships (interpretation)
F1 would enhance F17	Understands the importance of Industry 4.0 for their organization's growth and prosperity
F22 would lead to F2	By ensuring social sustainability benefits to the employee while adopting digital technologies
F5 would enhance F14	Ensure development of technology standards for eco-friendly production
F2 would enhance F19	Considers the organization's capabilities and enabling environment while adopting the digital technologies
F17 would enhance F12	Stakeholder engagement acts as an enabler for skill development and training programs
F3 would enhance F8	This would result in proper coordination of processes, systems, and workforce, allowing for decentralized decision-making
F12 would enhance F8	Build the capabilities among the employees for decentralized decision-making
F14 would enhance F4	Digital infrastructure is a prime requirement for the proper functioning of Industry 4.0
F16 would enhance F15	Ensure environment sustainability for the manufactured products
F18 would enhance F15	Effectively fulfill the demands of customer based on their choices
F13 would enhance F15	Delivering the green and efficient products in minimum possible time to end customers
F9 would enhance F16, F18, and F14	Implementation would bring sustainability benefits due to potential features and characteristics of digital technologies
F11 would enhance F9	Digital connectivity among different digital entities is crucial for the proper functioning of Industry 4.0
F7 would enhance F11	Digital integration would be achieved by an innovative and sustainable culture
F20 would enhance F11	Offering incentives/rewards to the employee would motivate them to opt for digital integration through digitalization
F21 would enhance F9	For the success of Industry 4.0, social benefits to the employee are also important

Appendix continued

Bilateral relationships between the factors	Reasons for the existence of relationships (interpretation)
F6 would enhance F21	Digital technologies adoption would bring social sustainable benefits to employee
F23 would enhance F6	To ensure safe operation and functioning of digital technologies within and external to the organization
F10 would enhance F6	To ensure safe operation and functioning of digital technologies within the organization
F4 would enhance F6	Digital infrastructure is the prime requirement for digital technologies functioning
F3 would enhance F10	Prepare the organization with adequate safety measure for data theft, fraud, and privacy issues
F14 would enhance F16	Development of digital technologies for achieving sustainability benefits
F11 would enhance F13	Digital integration would improve the organization's performance metrics
F17 would enhance F23	Stakeholder like the government is important to enforce effective legislative norms for data protection
Both the factors, F5 and F22 influence each other	Regulations pertaining to environmental sustainability and the workforce are essential for Industry 4.0 implementation
Both the factors, F22 and F1 influence each other	Framing of regulations needs support from top authorities of the organization
Both the factors, F2 and F17 influence each other	Framing of strategic roadmap for its sustainability is dependent upon collaborative support from various stakeholders
Both the factors, F14 and F3 influence each other	Integration of existing IT resources with emerging digital technologies through adoption of cutting-edge R&D practices would be required for effective organizational restructuring
Both the factors, F3 and F12 influence each other	Existing employees must be upskilled in order for the company to be successfully restructured in line with Industry 4.0
Both the factors, F4 and F8 influence each other	Employees would be able to make data-driven autonomous decisions if digital infrastructure is available in the organization
Both the factors, F10 and F23 influence each other	The successful implementation of Industry 4.0 requires the adoption of robust cybersecurity mechanisms and laws to resolve data theft issues

Appendix continued

Bilateral relationships between the factors	Reasons for the existence of relationships (interpretation)
Both the factors, F20 and F21 influence each other	Employee incentives and rewards are also critical for efficient adoption of digitalization techniques within the organization, so that social benefits, such as enhanced health and safety, can be realized
Both the factors, F16 and F18 influence each other	Industry 4.0 technologies for sustainable practices would aid in achieving flexible and mass tailored production
Both the factors, F18 and F13 influence each other	Adoption of digital technologies would aid in the production of lean and sustainable products, as well as assure faster and safer product delivery

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Declarations

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Key Questions

What role will Industry 4.0 technologies play in the sustainable development of manufacturing organizations?
What are the major impediments to implementing Industry 4.0 for sustainable production in Indian manufacturing organizations?
What are the advantages of implementing Industry 4.0 across different manufacturing sectors in terms of social, economic, and environmental benefits?

Veepan Kumar is an assistant professor in the Quantitative Techniques and Operations Management (QT&OM) area at FORE School of Management (FSM), New Delhi. He holds a Ph.D. in operations management from Indian Institute of Technology (IIT), Delhi. He has published a few research papers in international journal and has presented his research at international conferences in India and the USA. He has more than two years of teaching and research experience in the areas of Industry 4.0, digital supply chain, digitalization, and digital transformation of manufacturing organization.

Prem Vrat is the Pro-Chancellor; Professor of Eminence, and Chief Mentor at The NorthCap University, Gurugram (formerly ITM University, Gurugram). Prof. Prem Vrat was Founder-Director, IIT Roorkee; Vice-Chancellor, U.P. Technical University, Lucknow (now known as APJAKTU, Lucknow); Dean, Deputy Director and Director (Officiating) at IIT Delhi; Professor and Division Chairman of Asian Institute of Technology, Bangkok. He is an Honorary Professor at IIT Delhi and Distinguished Adjunct Professor at AIT, Bangkok. He has extensive experience of more than 52 years in teaching, research, management development, and consultancy. He has guided 49 PhD theses, 118 M.Tech, and 65 B.Tech major projects. He has authored/co-authored 7 books and published more than 500 research papers in reputed journals, international, and national conferences.

Ravi Shankar is the professor of operations and supply chain management in the Department of Management Studies, Indian Institute of Technology Delhi, India. He has published over 300 research papers with citations exceeding 34,713 as on July 2022 and an H-index of 77. He has authored/co-authored more than 6 books and published more than 300 papers in reputed journals, international, and national conferences. His areas of interest include decision sciences, business analytics and big data, operations and supply chain management, sustainable freight transportation, project management, total quality management and six sigma, strategic technology management, etc.