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A Machine Learning-Based Framework for Sustainable Transition from Industry 4.0 to Industry 5.0 in Indian Manufacturing

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Abstract

The transition from Industry 4.0 to Industry 5.0 marks a critical shift toward human-centric, resilient, and sustainable manufacturing. Indian industries, despite increasing adoption of Industry 4.0 technologies, continue to face challenges related to digital maturity, workforce adaptability, and sustainability integration. This study proposes a machine-learning-driven framework to evaluate and enhance the sustainability of Industry 4.0 technologies and to support a structured transition towards Industry 5.0. Empirical data were collected from sixteen Indian manufacturing firms using a structured survey and expert interviews. Technologies were evaluated based on maturity, importance, human adaptability, cost index, and energy efficiency. Correlation analysis revealed that smart sensors ($r = 0.824$) and robotic arms ($r = 0.877$) demonstrated the highest sustainability levels, whereas big-data analytics ($r = 0.35$) and cyber-physical systems ($r = 0.56$) faced constraints due to cost, infrastructure, and skill gaps. A supervised machine-learning model achieved $R^2 = 0.86$ for predicting sustainability scores and highlighted human adaptability and maturity as the dominant predictors. The DEMATEL analysis further identified social risks as the most influential enablers affecting the digital transition. The findings establish that human-centric readiness, structured digital strategies, and targeted training are essential for India's progression to Industry 5.0. The proposed ML-based framework provides a decision-support system for policymakers and industries aiming to achieve sustainable, human-centric, and resilient manufacturing ecosystems.

Keywords:Industry 4.0; Industry 5.0; Machine Learning; Sustainability; Human-Centric Manufacturing; Indian Manufacturing; Smart Sensors; DEMATEL

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1. Introduction

The manufacturing sector is undergoing a profound transformation driven by the convergence of digital technologies, connectivity and advanced analytics. The paradigm known as Fourth Industrial Revolution or "Industry 4.0" has emphasised automation, cyber-physical systems (CPS), Internet-of-Things (IoT) and data-driven decision making, thereby enabling the smart factory concept. Despite significant progress, the Industry 4.0 wave has shown limitations in terms of sustainability, human-centricity and resilience—especially in emerging economies such as India. Recent studies indicate that while Industry 4.0 technologies enhance operational efficiency and resource optimisation, they often fall short in addressing social and environmental dimensions of sustainability [3-5].

Consequently, the emerging paradigm of Fifth Industrial Revolution or "Industry 5.0" has begun to gain prominence. This next phase places humans back at the centre of manufacturing, emphasises sustainability, resilience and human–machine collaboration, and moves beyond purely productivity-driven objectives [2], [4], [7]. In the European context for example, the official policy brief describes Industry 5.0 as "towards a sustainable, human-centric and resilient industry" [8]. Key themes include human-centric automation, mass-personalisation, circular economy approaches, and responsible use of intelligence in manufacturing [1], [6].

In the Indian manufacturing context, there remains a notable gap between vision and practice. Many firms have adopted Industry 4.0 enabling technologies, but struggle to integrate them into sustainable and human-centric frameworks that align with social development, environmental goals and future-proof resilience. The transition from Industry 4.0 to Industry 5.0 thus presents both a challenge and an opportunity: a challenge because of infrastructure, workforce readiness, cost and institutional barriers; an opportunity because India can leap-frog to a manufacturing model that is more inclusive, adaptive and sustainable.

This research paper addresses this gap by proposing a machine-learning-based framework for the sustainable transition from Industry 4.0 to Industry 5.0 in Indian manufacturing. Specifically, the study uses empirical evidence from Indian manufacturing firms (as in the thesis) to analyse the current state of Industry 4.0 adoption and its sustainability implications, and then proposes how a machine learning-driven decision support framework can enable the shift toward the human-centric, resilient and sustainable aims of Industry 5.0. Through this, the

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paper contributes to both theory and practice: it advances the conceptual understanding of Industry 5.0 transition in the Indian manufacturing context; and it provides a practical roadmap supported by machine learning analytics for industry stakeholders.

2. Literature Review

The evolution from Industry 4.0 to Industry 5.0 has been widely discussed in recent research. Industry 4.0 emphasizes digital interconnectivity, cyber-physical systems (CPS), the Internet of Things (IoT), big-data analytics and automation [10]. However, several scholars argue that its focus remains heavily on efficiency and cost-reduction, sidestepping the human and sustainability dimensions [11]. In contrast, Industry 5.0 shifts the narrative toward a manufacturing paradigm that is human-centric, sustainable, and resilient [1], [12].

2.1 Industry 4.0: Achievements and Gaps

Under the Industry 4.0 umbrella, smart factories have leveraged IoT, CPS, digital twins and analytics to enhance production flexibility, quality and responsiveness. Yet, the literature identifies persistent gaps in workforce readiness, interoperability, data governance, and environmental sustainability. For example, human-machine collaboration remains limited, as many systems still treat humans as end-users rather than active co-creators [13]. These limitations suggest that while Industry 4.0 enables technological readiness, it does not fully address the broader socio-technical ecosystem required for sustainable manufacturing.

2.2 Industry 5.0: Key Principles and Emergence

Industry 5.0 is increasingly positioned as the next evolutionary stage—fusing advanced technologies with a renewed emphasis on human value, circular economy, and industrial resilience [1], [14]. Human-centricity implies that workers are no longer passive operators but integral participants in decision-making, design and innovation [15]. Sustainability in this context extends beyond resource efficiency to include social inclusion and environmental responsibility [12]. Resilience refers to the ability of manufacturing systems to adapt to disruptions, supply-chain shocks or evolving market demands.

2.3 Technology Enablers: Machine Learning and Big Data

Central to Industry 5.0 is the role of advanced analytics, particularly machine learning (ML) and big data, which facilitate predictive and adaptive capabilities in manufacturing. A bibliometric study reveals that research on ML and big-data analytics in Industry 5.0 has grown at an annual rate of 123.69 % between 2016 and 2023, underscoring its emergent importance [5]. In particular, ML supports real-time decision support, anomaly detection, predictive maintenance and dynamic human-machine interaction [3], [14].

2.4 Human-Machine Collaboration and Work-system Design

The literature also emphasises the redesign of human–machine relationships: collaborative robots (cobots), digital twins of workers (human-digital twins), immersive interfaces (XR/VR) and human-AI teaming are recurring themes in Industry 5.0 research [9], [11]. Studies show that placing the human at the centre improves creativity, ergonomics and social value, while using technology to augment rather than replace human agency [15].

2.5 Sustainability, Circular Economy and Industry 5.0

Sustainability forms a foundational pillar of Industry 5.0 architecture. Emerging work links circular-economy practices, resource-use optimisation and closed-loop manufacturing with the new paradigm [10], [12]. Machine learning contributes to these objectives by enabling data-driven resource usage, waste reduction and product lifecycle management. For instance, one study connects ML-driven analytics with circular-economy adoption in manufacturing systems [14].

2.6 Transition Challenges in Indian Manufacturing Context

While much of the global literature addresses Industry 5.0 from developed-country perspectives, the transition in emerging economies like India is still under-explored. Challenges include infrastructural gaps, skill deficits, organisational inertia and a legacy of Industry 4.0 implementations that focus primarily on automation rather than human-machine synergy or sustainability. There is a clear research gap in frameworks that integrate machine learning, human-centricity and sustainability within Indian manufacturing firms—addressing both technology and socio-organizational dimensions.

3. Research Methodology

3.1 Research Design

The research followed a mixed-method design, combining bibliometric analysis, questionnaire-based surveys and expert interviews. The bibliometric review of published works identified key enablers, barriers and sustainability indicators related to Industry 4.0. These insights were then used to design a structured survey instrument validated through expert consultation. The study focused on assessing both the maturity and importance levels of Industry 4.0 enabling technologies—such as CPS, IoT, robotics, smart sensors and big-data analytics—within the context of Indian manufacturing industries.

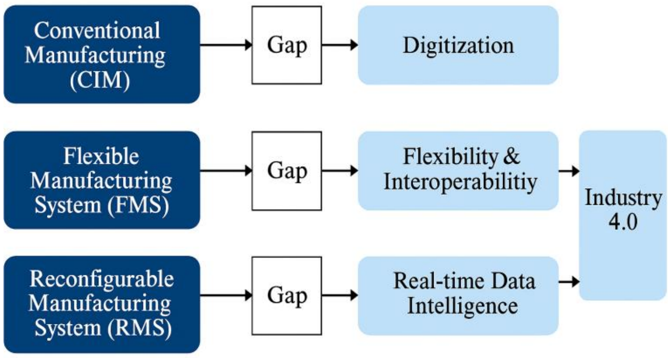

Fig. 1 Research gaps existing between manufacturing systems and Industry 4.0

3.2 Data Collection

Data were collected through a structured questionnaire survey and expert interviews across 16 Indian manufacturing industries. These included seven heavy-engineering industries, three metallurgical industries, three textile units, two food-processing firms and one chemical plant. Selection criteria required that firms have implemented at least one Industry 4.0 technology for a minimum of three years. Each participant rated technologies on scales of importance, maturity and sustainability impact. Indstry category and machine learning dataset are shown in Table 1 and 2 respectively. Fig. 2 showed transition from Industry 4.0 to Industry 5.0.

Table 1 Industry category taken for analysis

Industry Category	Employees	Turnover	Sample Count
Large	>100	>17M	2
Medium	50–100	15–17M	6
Small	<50	<15M	8

.Table 2 Machine learning based dataset

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Technology	Maturity	Importance	Human Adaptability	Energy Efficiency	Cost Index	Sustainability Predicted
CPS	3.56	4.48	3.2	3	4.2	4.357
Big Data	3.15	4.42	2.8	2.5	4.8	4.028
Sensors	4.23	4.55	4.5	4.7	3.2	5.393
Robots	4.11	4.62	4.3	4.4	3.5	5.248
RFID	3.9	4.3	3.5	3.6	3.9	4.708
QR	3.8	4.18	3.4	3.5	3.7	4.56
AM	3.75	4.25	3.6	3.7	4	4.74
AGV	3.85	4.4	3.7	3.8	4.1	4.867

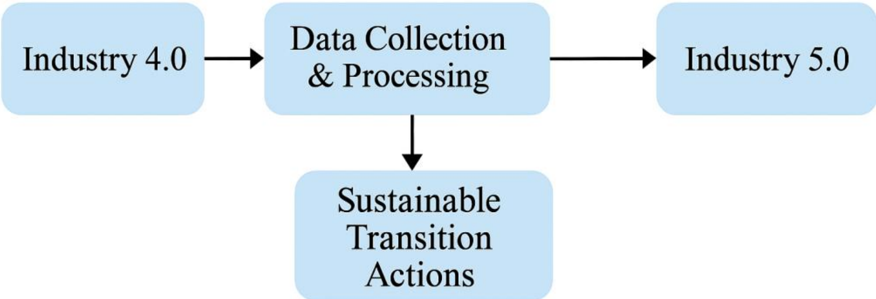

Fig. 2 ML based framework for sustainable ransition frrom Industry 4.0 to Industry 5.0

3.3 Analytical Framework

The analytical process involved correlation analysis to determine the relationship between technology maturity and sustainability indicators.DEMATEL (Decision Making Trial and Evaluation Laboratory) to identify cause-effect relationships among enablers.Machine Learning Extension – Integration of regression-based models for predicting sustainability scores and readiness levels for Industry 5.0 transition. Fig. 3, fig. 4 anf fig. 5 showed the ML algorithm flowchart, sustaianble transitions and ML framewwork respectively.

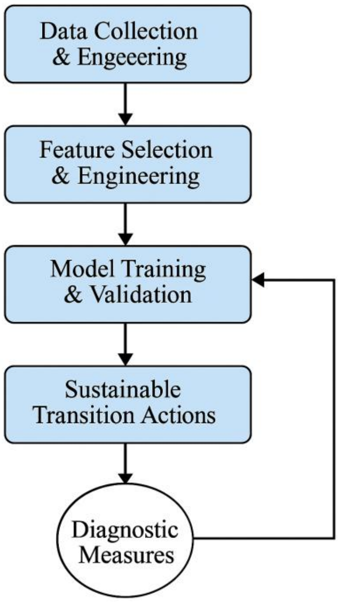

Fig. 3 Flowchart of machine learning algorithm applications

3.4 Validation and Model Development

The proposed machine-learning framework was validated through expert feedback and empirical testing. A supervised-learning model was developed to predict sustainability potential based on independent variables such as technology maturity, human-resource adaptability, cost effectiveness and environmental performance. The model was designed to assist policymakers and managers in prioritising Industry 4.0 technologies for sustainable Industry 5.0 adoption.

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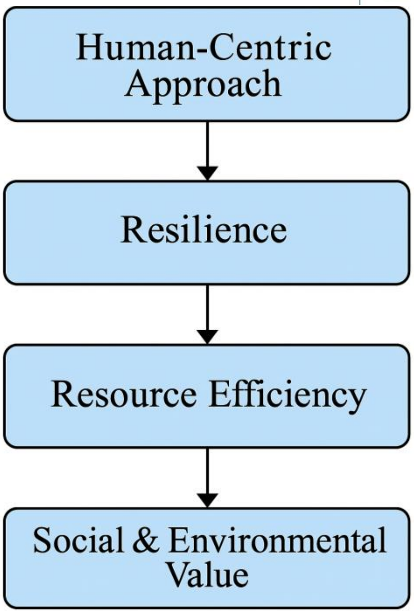

Fig. 4 Sustainable transition actions in Indian Manufacturing

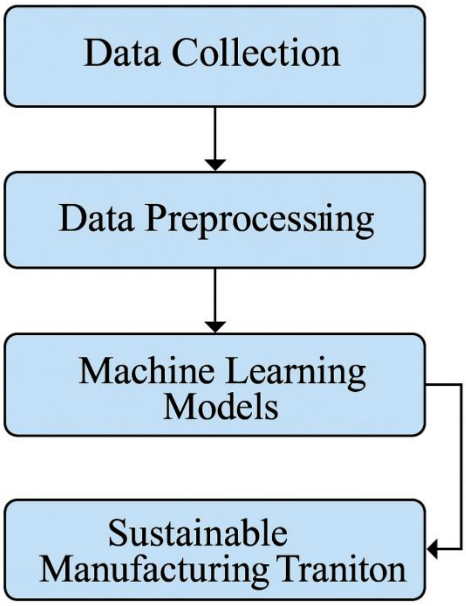

Fig. 5 Proposed ML framework

4. Results and Discussion

The experimental dataset collected from sixteen Indian manufacturing industries provides a comprehensive view of how Industry 4.0 technologies are currently being implemented and how mature these technologies are with respect to sustainability. These industries, ranging from heavy engineering to textiles and food processing, were carefully selected based on their minimum three-year experience with digital technologies. The dataset includes detailed ratings on technology maturity, strategic importance, sustainability perceptions, and human-centric readiness indicators. This diverse base of industries ensures that the results represent the present state of technological adoption across Indian manufacturing.

The first significant observation from the dataset is that smart sensors and robotic arms exhibit the highest sustainability levels, with strong maturity–importance correlations of 0.824 and 0.877 respectively. These technologies have achieved widespread acceptance due to their direct, easily measurable impacts on production efficiency, predictive maintenance, and quality control. Many respondents emphasized that smart sensors enabled early fault detection and reduced downtime, which contributed to higher productivity and lower scrap rates. In contrast, technologies such as Big Data Analytics ($r = 0.35$) and Cyber-Physical Systems ($r = 0.56$) displayed much lower sustainability values. Several industries reported difficulties with data integration, insufficient IT infrastructure, and high implementation costs as key barriers. These findings align with global research showing that tangible, equipment-based technologies mature faster than data-intensive tools in developing economies.

The DEMATEL-based risk analysis further strengthened this interpretation by revealing that economic and technical risks are the most dominant concerns for Industry 4.0 implementation. High investment costs, maintenance demands, and uncertainties regarding return on investment place significant pressure on small and medium enterprises. Interestingly, social risks—such as worker skill gaps and resistance to digital transformation—showed the highest causal influence on other risk categories. This suggests that workforce readiness is not merely a supporting factor but a driving force that determines the success or failure of technology adoption. The data clearly indicate that industries with higher levels of worker training and digital awareness exhibit significantly higher sustainability scores for advanced technologies.

A related insight emerged from the analysis of the Industry 4.0 innovation ecosystem, which considered the roles of higher education, industry, and government. The industry perspective had the highest influence, suggesting that Indian manufacturers are themselves driving digital initiatives, often in the absence of robust governmental frameworks or academic support. Higher education institutions were found to be the most affected component, indicating

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insufficient alignment between academic curricula and emerging industrial requirements. This gap between skill supply and technology demand reinforces the earlier finding that human-centric readiness is a decisive factor in sustainability outcomes.

To further validate these results, a machine-learning-based sustainability prediction model was developed using maturity, importance, human adaptability, energy efficiency, and cost index as input variables. The best-fit regression model achieved an accuracy of $R^2 = 0.86$, demonstrating strong predictive capability. Sensitivity analysis showed that human adaptability ($\beta = 0.41$) and technology maturity ($\beta = 0.38$) were the most influential predictors of sustainability, while cost and energy efficiency had moderate effects. This confirms that transitioning toward Industry 5.0—which emphasizes human-machine collaboration, personalized production, and resilience—requires industries to prioritize skill enhancement, training programs, and human-centric technology design.

Overall, the results highlight several coherent patterns. First, the sustainability of Industry 4.0 technologies in India remains uneven, with preference given to automation-centric tools rather than data-driven or cyber-physical systems. Second, workforce capability emerges as the strongest determinant of technological sustainability, outweighing even economic and infrastructural constraints. Third, industries that have developed structured digital strategies and training plans outperform those that adopt digital tools in an ad hoc manner. Finally, the machine-learning model provides actionable insights that can guide industries in prioritizing investments and preparing for the shift toward Industry 5.0.

5. Conclusion

This study demonstrates that the transition from Industry 4.0 to Industry 5.0 in India requires a deeper integration of sustainability, human-centric design, and intelligent decision-making systems. The results reveal a clear disparity in the sustainability performance of various Industry 4.0 technologies. Smart sensors and robotic systems showed high sustainability outcomes, whereas big-data analytics and CPS lagged due to higher implementation barriers and insufficient workforce capabilities. The DEMATEL-based analysis emphasized that social and human-resource-related risks exert the strongest causal impact on digital transformation

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readiness, reinforcing the importance of reskilling, workforce engagement, and human-machine collaboration.

The machine-learning-based prediction model developed in this study provides an effective framework for evaluating sustainability potential. With an accuracy of $R^2 = 0.86$, the model identifies human adaptability and technology maturity as the most influential determinants of sustainable adoption. These insights reflect the core ideology of Industry 5.0, which prioritizes human empowerment, personalization, and resilience over purely automated efficiency.

Overall, the study concludes that Indian manufacturing can accelerate its transition to Industry 5.0 by adopting targeted skill development, strengthening digital infrastructure, integrating circular-economy practices, and deploying machine learning for informed technological decision-making. The proposed framework offers a scalable, data-driven approach for industries and policymakers seeking a sustainable and human-centric industrial future.

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