

Industry 4.0 and Process Innovation: What Lies Ahead?

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1. Positioning of This Special Issue Within the Context of Industry 4.0

Industry 4.0 is now understood not merely as a project for productivity enhancement, but as a macroscopic paradigm shift that requires the simultaneous design of sustainable innovation and process optimization. According to a recent systematic literature review, Industry 4.0 technologies serve as key drivers of a “sustainable innovation roadmap” by not only improving process automation and quality but also fostering eco-process innovation and strengthening organizational capabilities—such as knowledge bases, green absorptive capacity, and sustainable partnerships [1].

Another comprehensive review focusing on the manufacturing shop floor presents a five-layer conceptual framework suggesting that the adoption of smart sensors, data analytics, and cyber–physical systems (CPSs) should simultaneously target environmental and social performance alongside lead time reduction, quality enhancement, and organizational performance improvement [2]. Simultaneously, data analytics based on machine learning and deep learning are regarded as critical tools for enhancing efficiency across a broad spectrum of manufacturing operations—including predictive maintenance, quality control, scheduling, and supply chain management—without significantly increasing resource inputs [3].

Within this context, the topics addressed in this Special Issue—types of process innovation [4], transition strategies based on smart factory maturity models (e.g., SIRI) [5], AI-based anomaly detection [6], trends in global supply chains [7] and port/factory automation [8,9], and case studies on battery manufacturing processes [10]—align along a central axis examining the “concrete implementation methods for innovation and optimization in the Industry 4.0 era”.

The collection of papers presented in this Special Issue has allowed us to derive several critical insights. First, it highlights that environmental innovation is a pivotal prerequisite for driving broader innovation. Specifically, there is a compelling need for continued research into how diverse types of environmental innovation impact corporate innovation performance and subsequently translate into innovation efficiency.

Furthermore, the contributions suggest that rather than a blind adoption of Industry 4.0, organizations must evaluate their transition maturity using tools such as the Smart Industry Readiness Index (SIRI). In addition, as the utilization of various AI technologies is indispensable in Industry 4.0, time-series-based anomaly detection in industrial control systems utilizing Generative Adversarial Networks (GANs) emerges as a significant research imperative.

However, these dynamics are not confined to domestic contexts. Given the increasing complexity and automation of supply chains, analyzing global factory automation trends is essential. It was also argued that accurate performance measurement requires looking beyond individual contracts or transactional relationships to consider the broader network structure within the supply chain. In practice, ports—which constitute a major element of



Received: 2 December 2025

Accepted: 4 December 2025

Published: 11 December 2025

Citation: Kim, C. Industry 4.0 and Process Innovation: What Lies Ahead? *Processes* **2025**, *13*, 4011. <https://doi.org/10.3390/pr13124011>

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the supply chain—are optimizing asset management using Building Information Modeling (BIM) and Geographic Information Systems (GIS), while factory automation trends are being analyzed through text mining of patent data. The Special Issue also reports on specific manufacturing cases, such as the measurement of the State of Charge (SoC) for lithium batteries, which is deeply integrated with electric vehicle manufacturing.

Based on these discussions, how should we proceed? What specific lines of inquiry must be pursued to successfully realize Industry 4.0 innovation and optimization from the perspective of manufacturing processes? This Editorial aims to present key questions and instigate discourse regarding these critical issues.

2. First Consideration: Designing Process Innovation Styles Tailored to Industry Characteristics

The Oslo Manual’s definition of innovation—characterizing it not as a singular event but as a continuous process, and distinguishing between product, process, marketing, and organizational innovations while emphasizing their interplay and ecosystem—resonates deeply with the transition to Industry 4.0 [11]. Recent research consistently demonstrates that Industry 4.0 technologies are effective not merely through the acquisition of equipment, but when implemented as part of a co-evolutionary process involving the organization, processes, and business models [12]. This perspective underscores that a uniform “standard process innovation” does not exist; instead, process innovation must be co-designed with organizational culture, values, and structure. While process innovation inherently dictates cost, quality, and flexibility, the actual success of implementation relies heavily on the “fit with the organizational value system.” For instance, research indicates that the configuration of organizational values (e.g., flexibility vs. control, collaboration vs. performance) and their mutual fit significantly determine the performance of advanced manufacturing technology adoption [13].

This principle of organizational fit applies directly to Industry 4.0-type process innovation, particularly regarding the balance between performance and welfare. For example, if highly automated equipment is introduced alongside high-intensity performance management, it may yield short-term efficiency but can generate adverse effects regarding fatigue, safety, and skill accumulation. Conversely, in an environment where autonomy and a learning-oriented culture are established, increasing process data transparency and designing systems where field workers utilize AI-based decision support to self-improve processes can better achieve a balance between performance and welfare. Therefore, process innovation must be designed as a triad of technology, organization, and culture to simultaneously optimize this balance.

Beyond the internal organizational context, innovation styles must also diverge based on industry and supply chain positioning. In capital-intensive process industries with high fixed asset ratios and substantial downtime costs, priority is placed on incremental process innovation and the enhancement of process stability and resilience. Empirical studies report that Industry 4.0 capabilities enhance supply chain resilience by mediating this incremental innovation [14]. In contrast, for assembly and processing industries characterized by high-mix, low-volume production, process innovation combined with flexible production, mass customization, and supply chain integration becomes paramount [15]. Here, “Lean Automation” has been shown to simultaneously improve productivity, lead time, inventory, and quality performance [16]. Finally, in highly regulated industries (e.g., glass, chemicals, batteries) with high raw material intensity, the process innovation style must be designed with the Circular Economy and resource optimization as prerequisites. Research suggests that integrating Industry 4.0 with supply chain integration significantly improves Circular Economy performance [17,18]. Thus, clearly defining a “process innovation style tailored

to one's specific industry and supply chain position" constitutes the core task of this first consideration.

3. Second Consideration: Evaluation Systems for Measuring Innovation Efficiency and Process Optimization

The transition to Industry 4.0 typically involves high-cost, high-risk investments where the return on investment is not always immediately visible. Despite this reality, many enterprises continue to evaluate innovative performance based on simplistic metrics—such as Units Per Hour (UPH), Overall Equipment Effectiveness (OEE), or the mere adoption status of IT systems. However, recent literature indicates that such limited evaluation methods fail to capture the “invisible performance” aspects critical to Industry 4.0, including sustainability, process flexibility, knowledge accumulation, and supply chain resilience [3]. To address this limitation, research reviewing the intersection of sustainable manufacturing and Industry 4.0 suggests that corporate evaluation systems must encompass at least four dimensions: technical and data capabilities (automation, IoT, AI), operational performance (lead time, quality, resource efficiency), sustainable performance (carbon reduction, circularity, safety), and organizational/strategic performance (innovation culture, partnerships). This implies that “innovation efficiency” should be understood not merely as a simple input–output ratio, but as an integrated system evaluating these multi-dimensional performance metrics.

Furthermore, indicator design must incorporate maturity and Supply Chain 4.0 perspectives. Studies establishing the Supply Chain 4.0 concept propose a maturity framework structured around management enablers, technology levers, process performance requirements, and strategic performance [19]. Similar to the Smart Industry Readiness Index (SIRI), this approach facilitates the systematic plotting of a roadmap from current to target levels through gap analysis, enabling an integrated diagnosis of both manufacturing processes and supply chains. Additionally, research focusing on risk and the ripple effect analyzes how digital technologies—such as big data analytics, tracking systems, and advanced manufacturing—can facilitate the early detection of supply chain disruptions and optimize recovery strategies [20]. This suggests that evaluation systems must measure not only “current efficiency” but also “resilience” against crises.

In summary, the second critical consideration lies in establishing a “meta-indicator system” that simultaneously measures the transition maturity and innovation efficiency of smart factories and supply chains. This system must encompass perspectives on processes, organization, supply chains, sustainability, and risk management, necessitating the complementary integration of frameworks such as SIRI, smart factory maturity diagnostics, and innovation performance models discussed in this Special Issue.

4. Third Consideration: Feedback, Learning, and Investment for the Future

For Industry 4.0 innovation to succeed, it is imperative to construct continuous feedback loops derived from the vast data generated by processes and to design future investments based on these insights. This mechanism revolves around three principal axes: AI-based anomaly detection and predictive maintenance, network-level feedback from supply chain and circular economy perspectives, and learning and scaling up from specific manufacturing cases such as lithium-ion batteries.

First, time-series-based anomaly detection serves as the “sensory organ” and core infrastructure of the smart factory. Recent advancements emphasize methods that simultaneously consider the temporal axis (time-series) and structural relationships (graphs) within complex industrial systems. For instance, a recent survey highlights that the “G-TSAD” approach—which models variable interdependencies in time-series data as graphs and

utilizes deep learning and graph neural networks (GNNs)—significantly enhances performance in diverse industrial applications [21]. To address the scarcity of anomalous data and the emergence of unknown novel anomalies in real-world environments, data augmentation techniques employing adversarial learning have been proposed. These methods, which generate adversarial examples to retrain HMM-based detectors, have been reported to statistically improve detection performance and robustness against adversarial attacks in multivariate time-series contexts [22]. Furthermore, in the realm of Industrial IoT (IIoT), federated learning-based deep anomaly detection frameworks offer a solution that maintains the generalization performance of global models while preserving privacy and minimizing communication costs [23]. Additionally, advanced methodologies combining autoencoders with Wasserstein GANs for rotating machinery [24], and predictive anomaly detection combining waveform decomposition with Koopman theory for nonstationary systems like liquid rocket engines [25], demonstrate superior accuracy. Collectively, these studies suggest that the “GAN-based time-series anomaly detection” discussed in this Special Issue must evolve from a mere methodological topic into a comprehensive “intelligent sensory and diagnostic infrastructure.” Future research must link these advanced models with SIRI or maturity assessments to define “what level of AI infrastructure is required for a specific factory level” and integrate them with organizational culture to create a feedback loop where technology, people, and organizations learn together.

Second, feedback loops must be established from the perspective of the supply chain and the Circular Economy (CE). Adopting Industry 4.0 technologies across the supply chain facilitates the transition to Supply Chain 4.0, acting as a critical mediator for promoting sustainability beyond mere efficiency. Systematic literature reviews indicate that combining Industry 4.0 technologies with Supply Chain Integration (SCI) accelerates circular practices such as raw material reuse, waste tracking, and demand forecasting precision [26]. As evidenced by the glass industry case study [17], research is increasingly analyzing the key enablers and causal structures required to implement “Supply Chain 4.0 + CE”. This supports the argument that accurate performance measurement requires considering the network structure of the supply chain beyond individual contracts. Digital transformation in ports, asset management utilizing BIM and GIS, digital twins, and the analysis of global automation trends via patent text mining all function as critical nodes in this network-level feedback loop. Future research should focus on developing integrated dashboard systems that combine real-time data from supply chain gateways with SIRI, SCM maturity models, and CE metrics to simultaneously track “innovation efficiency and sustainable performance in Supply Chain 4.0”.

Finally, specific manufacturing cases, such as the production of lithium-ion batteries for electric vehicles, serve as critical testbeds for Industry 4.0 innovation. In this high-value, high-risk domain, key issues include estimating State of Charge (SOC) and State of Health (SOH) using equivalent circuit models, Kalman filters, and impedance analysis; quantifying complex interactions between process conditions, materials, and lifecycle characteristics; and leveraging massive process data for prediction and optimization. A crucial task ahead is to interconnect these specific engineering cases with the broader frameworks of process innovation, evaluation systems, anomaly detection, and supply chain/circular economy research discussed previously, thereby facilitating learning and scale-up across the manufacturing sector.

5. Conclusions

Based on the discussions presented in this Special Issue and preceding literature, we propose three pivotal directions for future research regarding Industry 4.0 innovation and process optimization.

First, research must advance towards a sophisticated typology of process innovation styles tailored to specific industries and supply chains. By synthesizing diverse contextual factors—including organizational culture and values, process characteristics (continuous vs. discrete; process vs. assembly), regulatory and environmental constraints, and supply chain positioning (raw materials, components, finished goods, or services)—scholars should aim to derive distinct “Process Innovation Archetypes”. Subsequent studies should then propose optimal strategies for Industry 4.0 technology adoption, organizational design, and human resource management suited to each specific archetype.

Second, the establishment of a “meta-evaluation system” that integrates maturity, performance, sustainability, and risk is essential. We call for the development of a multi-layered framework that combines the Smart Industry Readiness Index (SIRI), Supply Chain 4.0 maturity models, sustainable manufacturing metrics, and supply chain resilience indicators. Empirical research applying this framework to actual enterprises and industries is urgently required. Furthermore, this line of inquiry should extend to practical applications, such as alignment with government policies and support schemes, the determination of priorities for innovation investment, and the formulation of specific support strategies for Small and Medium-sized Enterprises (SMEs).

Third, research must bridge the gap between AI-based anomaly detection/predictive maintenance and Circular Economy (CE) or business model innovation. Leveraging advanced AI techniques—such as GANs, Graph Neural Networks (GNNs), Federated Learning, and Koopman-based time-series analysis—future studies should design data-driven feedback loops. These loops must expand beyond mere process anomaly detection to encompass asset lifecycle management and circular business models, including remanufacturing and reuse. This integration will serve as the foundational basis for Industry 4.0 to transcend process efficiency and evolve into a sustainable and resilient manufacturing and supply chain ecosystem.

Ultimately, these three directions represent an attempt to integrate the three concerns raised in this editorial—innovation styles tailored to industries, innovation evaluation systems, and the issues of feedback and future investment—not as isolated tasks, but as a single, continuous innovation process. We anticipate that future research and policy discussions will envision the future of Industry 4.0 and smart factories through this integrated and holistic lens.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflicts of interest.

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