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A Study On AI-Driven Green Innovation In Manufacturing Industries

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Abstract

Manufacturing industries are at the center of global economic growth but are also major contributors to environmental degradation, carbon emissions, and resource depletion. The increasing urgency of climate change, stricter environmental regulations, and rising stakeholder expectations have compelled manufacturers to rethink traditional production models. Artificial Intelligence (AI) has emerged as a transformative technology capable of enabling green innovation by improving energy efficiency, reducing waste, optimizing supply chains, and facilitating sustainable product design.

This conceptual paper explores how AI drives green innovation in manufacturing industries. Drawing upon theoretical foundations such as the Resource-Based View (RBV), Dynamic Capabilities Theory, and Stakeholder Theory, the paper develops a comprehensive conceptual framework linking AI capabilities to sustainable manufacturing performance and competitive advantage. It discusses enabling technologies, strategic integration, benefits, barriers, and future research directions. The study concludes that AI-driven green innovation is not merely a technological upgrade but a strategic necessity for sustainable industrial transformation.

Introduction

Manufacturing industries have long been recognized as engines of economic growth, technological advancement, and employment generation. From heavy industries such as steel and cement to high-technology sectors such as electronics and automotive production, manufacturing forms the backbone of national and global economies. However, this industrial expansion has come at a significant environmental cost. High energy consumption, greenhouse gas emissions, excessive water usage, hazardous waste generation, and resource depletion have made the manufacturing sector one of the largest contributors to environmental degradation. As global climate change intensifies and natural resources become increasingly scarce, the need for sustainable transformation within manufacturing industries has become urgent and unavoidable.

In response to these challenges, the concept of green innovation has emerged as a strategic approach to reconcile industrial productivity with environmental responsibility. Green innovation refers to the development and implementation of new or improved products, processes, technologies, and managerial practices that reduce environmental impact while maintaining or enhancing economic performance. It involves minimizing waste, improving energy efficiency, using renewable resources, adopting cleaner production methods, and designing eco-friendly products. Governments, regulatory bodies, investors, and consumers are increasingly demanding that manufacturing firms integrate sustainability into their core business strategies. Consequently, green innovation is no longer optional; it has become a competitive necessity.

Simultaneously, the manufacturing sector is undergoing a digital transformation driven by Industry 4.0 technologies, among which Artificial Intelligence (AI) plays a central role. AI encompasses a range of technologies—including machine learning, predictive analytics, robotics, computer vision, and intelligent automation—that enable machines and systems to perform tasks that traditionally required human intelligence. In manufacturing environments, AI systems can analyze large volumes of real-time data, detect patterns, predict equipment failures, optimize production schedules, and improve operational efficiency. These capabilities position AI as a powerful enabler of sustainability initiatives. Beyond operational improvements, AI-driven green innovation also has strategic implications. Firms that successfully integrate AI into their sustainability strategies can achieve cost reductions, improved productivity, enhanced brand reputation, regulatory compliance, and long-term competitive advantage. Investors increasingly consider Environmental, Social, and Governance (ESG) performance in decision-making, and AI provides measurable data to support sustainability reporting and transparency. Thus, AI not only contributes to environmental performance but also strengthens overall business resilience and profitability.

Despite its significant potential, the adoption of AI-driven green innovation is not without challenges. High implementation costs, lack of skilled workforce, data security concerns, integration complexities, and resistance to technological change may hinder progress, particularly among small and medium-sized enterprises. Moreover, ethical considerations related to data governance and responsible AI usage must be carefully addressed to ensure that technological advancement aligns with social values.

In conclusion, the convergence of artificial intelligence and green innovation represents a transformative shift in manufacturing paradigms. As environmental sustainability becomes a global priority, AI has the potential to redefine how manufacturing industries operate, compete, and contribute to society. The following sections of this paper will examine the conceptual background, theoretical perspectives, enabling technologies, and strategic pathways through which AI can drive sustainable innovation in manufacturing sectors.

Literature Background

Artificial Intelligence (AI) has emerged as a transformative force in manufacturing, reshaping traditional production paradigms by enabling smarter, more flexible, and highly adaptive systems. Early research in manufacturing focused on automation and computer-integrated manufacturing, but recent studies underscore AI's role in enhancing decision-making, process optimization, and predictive capabilities across the value chain. Machine learning, deep learning, and data analytics are widely cited as key enablers for real-time quality control, predictive maintenance, and supply chain optimization, facilitating reductions in downtime and production costs while improving product quality (e.g., Lee et al., 2018; Zhong et al., 2017). The integration of AI with cyber-physical systems and the Industrial Internet of Things (IIoT) has further intensified innovation by enabling autonomous, self-learning systems that adapt to environmental changes and operational uncertainties. Scholars also highlight the strategic implications of AI adoption, noting its potential to foster mass customization, accelerate innovation cycles, and create new business models through smart factories and digital twins. Concurrently, literature emphasizes barriers to implementation, including data governance challenges, workforce skill gaps, and integration complexities, suggesting that realizing AI's full potential requires aligned technological, organizational, and human factors research.

Collectively, these studies frame AI not merely as a technological upgrade but as a foundational driver of Industry 4.0, positioning intelligent systems at the core of modern manufacturing competitiveness.

Extensive empirical and conceptual studies highlight AI's role in enhancing operational performance through predictive maintenance, intelligent process control, demand forecasting, and supply chain optimization. Researchers emphasize that AI-driven systems reduce downtime, improve product quality, enhance flexibility, and enable mass customization. The literature also explores digital twins—virtual representations of physical assets—that use AI algorithms to simulate and optimize production processes before real-world implementation. Beyond operational improvements, scholars increasingly frame AI as a strategic innovation driver that reshapes business models, enabling servitization , platform-based ecosystems, and data-driven value creation. Sustainability-oriented research further connects AI adoption to green manufacturing, demonstrating its potential to reduce energy consumption, minimize waste, and support circular economy practices.

Theoretical discussions commonly draw upon the Resource-Based View (RBV), Dynamic Capabilities Theory, and socio-technical systems theory to explain how firms leverage AI resources and organizational capabilities to achieve competitive advantage. At the same time, the literature acknowledges significant challenges, including data integration complexity, cybersecurity risks, skill shortages, high investment costs, and ethical concerns surrounding workforce displacement and algorithmic transparency. Recent studies call for interdisciplinary approaches and longitudinal analyses to better understand the long-term impact of AI on innovation performance and industrial sustainability. Overall, the literature positions AI-driven innovation as a transformative force that not only enhances operational efficiency but fundamentally reconfigures manufacturing systems, organizational structures, and competitive dynamics in the digital era.

Theoretical Foundations

The theoretical foundation of AI-driven innovation in manufacturing industries is grounded in multiple complementary perspectives that explain how advanced technologies create competitive advantage, organizational transformation, and industrial evolution. The Resource-Based View (RBV) provides a primary lens, suggesting that AI capabilities—such as proprietary algorithms, data assets, technical expertise, and digital infrastructure—constitute valuable, rare, inimitable, and non-substitutable (VRIN) resources that enable firms to achieve sustained competitive advantage. Extending RBV, the Dynamic Capabilities framework emphasizes a firm's ability to integrate, build, and reconfigure internal and external competencies to respond to rapidly changing technological environments; AI enhances sensing (through predictive analytics), seizing (through intelligent decision-making), and transforming (through process automation and business model innovation). The Technology-Organization-Environment framework (TOE) further explains AI adoption by highlighting how technological readiness, organizational support, and environmental pressures (e.g., market competition and regulatory forces) collectively shape implementation outcomes in manufacturing contexts.

From a socio-technical perspective, Socio-Technical Systems Theory posits that effective AI integration requires alignment between technological systems and human actors, emphasizing workforce skills, organizational culture, and collaborative human–machine interaction. The Diffusion of Innovations theory explains how AI technologies spread across manufacturing firms based on perceived relative advantage, compatibility, complexity, trialability, and observability. In the context of digital transformation, Industry 4.0 serves as a macro-level conceptual framework describing the convergence of AI, cyber-physical systems, robotics, and the Industrial Internet of Things into smart, autonomous production systems. Additionally, Absorptive Capacity theory highlights the importance of a firm's ability to recognize, assimilate, and apply external knowledge—critical for leveraging AI innovations effectively. Together, these theoretical perspectives frame AI-driven innovation in manufacturing as a multidimensional phenomenon involving strategic resource development, adaptive capabilities, organizational readiness, environmental alignment, and continuous learning, thereby explaining both its transformative potential and the conditions necessary for successful implementation.

AI Technologies Enabling Green Manufacturing

AI-driven innovation plays a central role in advancing green manufacturing by enabling intelligent, data-driven approaches to resource efficiency, waste reduction, and environmental sustainability. At the core of this transformation are machine learning (ML) and deep learning algorithms that analyze large volumes of production, energy, and emissions data to optimize processes in real time. For example, predictive analytics models forecast energy consumption patterns and dynamically adjust machine operations to minimize electricity usage, thereby reducing carbon footprints. AI-powered predictive maintenance systems detect equipment inefficiencies and prevent breakdowns, which not only lowers maintenance costs but also reduces material waste and unnecessary energy consumption. Computer vision technologies enhance quality control by identifying defects early in the production cycle, minimizing scrap rates and rework, which directly contributes to resource conservation.

Furthermore, AI integrated with the Industrial Internet of Things (IIoT) enables smart energy management systems that monitor and regulate energy flows across factories, supporting the integration of renewable energy sources such as solar and wind into manufacturing operations. Reinforcement learning algorithms optimize production scheduling to reduce peak energy loads and emissions, while digital twins simulate manufacturing processes to evaluate environmental impacts before physical implementation, enabling eco-efficient product and process design. AI also enhances circular economy practices by improving material tracking, automated sorting, and recycling systems through intelligent robotics and data analytics. In supply chain management, AI-driven demand forecasting and route optimization reduce overproduction, excess inventory, and transportation-related emissions.

Additionally, natural language processing (NLP) tools assist firms in monitoring environmental regulations and sustainability reporting requirements, improving compliance and transparency. AI-based life cycle assessment (LCA) models support sustainable product development by evaluating environmental impacts across raw material extraction, production, usage, and end-of-life stages. Collectively, these AI technologies enable manufacturers to transition from reactive environmental management to proactive, predictive, and optimized green manufacturing systems. The literature increasingly recognizes AI not merely as a productivity tool but as a strategic enabler of sustainable industrial transformation, aligning economic performance with environmental stewardship and long-term sustainability goals.

Benefits of AI-Driven Green Innovation

AI-driven green innovation in manufacturing industries delivers multidimensional benefits that extend across environmental, economic, operational, and strategic domains. Environmentally, AI enhances energy efficiency through intelligent energy management systems that monitor real-time consumption patterns and automatically optimize machine performance, significantly reducing greenhouse gas emissions and carbon footprints. Advanced analytics and predictive maintenance minimize material waste, prevent equipment failures, and reduce resource overuse, contributing to cleaner production processes. AI-supported life cycle assessment and eco-design tools enable manufacturers to develop sustainable products by evaluating environmental impacts from raw material sourcing to end-of-life disposal, thereby strengthening circular economy practices such as recycling, remanufacturing, and reuse. Economically, AI-driven green innovation lowers operational costs by reducing energy bills, minimizing scrap and rework, optimizing logistics routes, and improving supply chain efficiency. These cost savings enhance profitability while simultaneously meeting sustainability targets. Strategically, firms adopting AI-enabled green practices gain competitive advantage by complying more effectively with environmental regulations, improving ESG (Environmental, Social, and Governance) performance, and strengthening corporate reputation among environmentally conscious consumers and investors. Operationally, AI increases production flexibility and resilience by enabling real-time decision-making, adaptive scheduling, and data-driven forecasting, which reduce overproduction and inventory waste. Furthermore, AI fosters innovation in business models, such as servitization and sustainable product-service systems, where predictive analytics supports maintenance-as-a-service and resource-sharing platforms.

Socially, AI-driven green innovation can promote safer workplaces through automated hazardous-task handling and intelligent monitoring systems that reduce environmental and occupational risks. Overall, AI-driven green innovation transforms manufacturing from a resource-intensive, pollution-prone system into an intelligent, efficient, and sustainability-oriented ecosystem, aligning long-term economic growth with environmental stewardship and responsible industrial development.

Challenges and barriers

AI-driven innovation in manufacturing industries faces numerous challenges and barriers that span technological, organizational, economic, ethical, and regulatory dimensions. Technologically, one of the primary obstacles is data-related complexity, as AI systems require large volumes of high-quality, structured, and real-time data; however, many manufacturing firms operate with legacy equipment that lacks interoperability and standardized data formats. Integrating AI with existing enterprise systems, robotics, and cyber-physical infrastructure is often costly and technically demanding, increasing implementation risks. Cybersecurity vulnerabilities also intensify as interconnected smart factories expand digital attack surfaces, raising concerns about data breaches and operational disruptions. From an organizational perspective, resistance to change and lack of digital culture hinder adoption, particularly in traditional manufacturing environments where employees may perceive AI as a threat to job security. A significant skills gap further constrains progress, as successful AI deployment requires expertise in data science, machine learning, systems integration, and domain-specific engineering knowledge, which many firms struggle to acquire or develop.

Economically, high upfront investment costs for AI infrastructure, cloud computing, advanced sensors, and training programs present financial barriers, especially for small and medium-sized enterprises (SMEs). Uncertain return on investment (ROI) and unclear performance metrics make strategic decision-making more complex. Additionally, ethical and governance issues, including algorithmic bias, transparency, accountability, and workforce displacement, generate managerial and societal concerns. Regulatory compliance and evolving data protection laws add another layer of complexity, particularly when AI systems process cross-border data. Furthermore, scalability challenges arise when pilot AI projects fail to transition effectively into full-scale industrial implementation due to lack of strategic alignment or cross-functional coordination. Supply chain fragmentation can also limit the effectiveness of AI systems that rely on integrated data flows among partners. Collectively, these barriers highlight that AI-driven innovation in manufacturing is not solely a technological challenge but a comprehensive socio-technical transformation requiring strategic leadership, workforce reskilling, robust governance frameworks, and long-term investment commitment to ensure sustainable and successful adoption.

Proposed Conceptual Framework

A proposed conceptual framework for AI-driven innovation in manufacturing industries can be structured as an integrated, multi-layered model that links technological capabilities, organizational readiness, environmental drivers, and sustainability outcomes. At the foundational level, the framework positions AI technological capabilities—such as machine learning algorithms, predictive analytics, computer vision, digital twins, and Industrial Internet of Things (IIoT) integration—as key enablers that transform raw data into actionable intelligence. These capabilities are supported by critical infrastructure elements including data quality, cloud computing, cybersecurity systems, and interoperable cyber-physical systems. The second layer emphasizes organizational enablers, including top management support, digital leadership, employee skills and training, absorptive capacity, and a culture of innovation, which collectively determine the firm's readiness to adopt and scale AI solutions. This layer also incorporates strategic alignment, ensuring that AI initiatives are integrated with corporate sustainability goals and long-term competitive strategies.

The third layer of the framework introduces environmental and external drivers such as regulatory pressure, market competition, customer demand for sustainable products, technological turbulence, and supply chain collaboration. These external forces influence both the speed and direction of AI adoption.

The interaction among technological capabilities, organizational readiness, and environmental drivers leads to AI-enabled process innovations (e.g., predictive maintenance, intelligent scheduling, energy optimization), product innovations (e.g., eco-designed and smart products), and business model innovations (e.g., servitization and circular economy models). These innovation outputs subsequently generate multidimensional performance outcomes, including operational efficiency, environmental sustainability (reduced emissions, waste minimization, resource efficiency), economic performance (cost reduction, profitability), and strategic performance (competitive advantage, resilience, and brand reputation). The framework also incorporates feedback loops, where improved performance strengthens organizational learning and further enhances AI capability development, creating a continuous innovation cycle. Overall, this conceptual framework presents AI-driven innovation in manufacturing as a dynamic, socio-technical system in which technology, organization, and environment interact to produce sustainable industrial transformation and long-term value creation.

Managerial Implications

AI-driven innovation in manufacturing industries carries significant managerial implications that require strategic foresight, organizational transformation, and capability development. First, managers must adopt a clear digital strategy that aligns AI initiatives with long-term business objectives, sustainability goals, and competitive positioning, rather than treating AI as a standalone technological upgrade. This involves prioritizing high-impact use cases such as predictive maintenance, intelligent quality control, and energy optimization, while establishing measurable performance indicators to evaluate return on investment and sustainability outcomes. Leadership commitment is critical; top management must champion digital transformation, allocate sufficient financial and human resources, and foster a culture that encourages experimentation and data-driven decision-making. Managers should also invest in workforce reskilling and upskilling programs to address the digital skills gap, promoting collaboration between data scientists, engineers, and production staff to ensure effective human–AI integration.

Additionally, managers must strengthen data governance frameworks to ensure data quality, cybersecurity, privacy compliance, and ethical AI usage, thereby mitigating operational and reputational risks. Cross-functional integration is essential, as AI implementation often requires coordination among IT, operations, supply chain, R&D, and sustainability departments. Managers should also build strategic partnerships with technology providers, research institutions, and supply chain partners to access external expertise and accelerate innovation. For small and medium-sized enterprises (SMEs), phased implementation strategies and pilot projects can reduce financial risk while enabling gradual capability development. From a sustainability perspective, managers should integrate AI into green manufacturing initiatives by leveraging intelligent systems to monitor energy consumption, reduce waste, and support circular economy practices. Finally, continuous learning mechanisms—such as performance feedback loops, innovation labs, and digital maturity assessments—should be established to ensure scalability and long-term adaptability. Overall, managerial action must move beyond technology adoption toward orchestrating organizational change, ecosystem collaboration, and strategic alignment to fully realize the transformative potential of AI-driven innovation in manufacturing.

Future Research Directions

Future research on AI-driven innovation in manufacturing industries should move beyond adoption-focused studies toward deeper theoretical, empirical, and interdisciplinary exploration. First, there is a need for longitudinal studies that examine how AI capabilities evolve over time and how they influence sustained competitive advantage, organizational resilience, and long-term sustainability performance. Many existing studies rely on cross-sectional data; future research should investigate dynamic capability development, learning mechanisms, and scaling pathways from pilot projects to enterprise-wide AI integration. Second, scholars should develop more robust measurement models and validated constructs for assessing AI maturity, digital readiness, and AI-driven innovation performance, particularly in small and medium-sized enterprises (SMEs) and emerging economies where contextual differences remain underexplored.

Another important research direction involves examining the integration of AI with green manufacturing and circular economy models, focusing on quantifying environmental outcomes such as carbon reduction, energy efficiency, and waste minimization through empirical and simulation-based approaches. Future studies should also explore human–AI collaboration in smart factories, including workforce transformation, skill reconfiguration, job redesign, and ethical implications related to algorithmic transparency, accountability, and bias. Interdisciplinary research combining operations management, information systems, sustainability science, and organizational behavior could provide more comprehensive insights into socio-technical alignment challenges.

Furthermore, research should investigate AI governance frameworks, cybersecurity resilience, and regulatory adaptation in increasingly interconnected manufacturing ecosystems. Comparative cross-country studies could reveal how institutional environments, policy incentives, and industrial structures influence AI adoption and innovation outcomes. Emerging technologies such as generative AI, edge computing, federated learning, and explainable AI also warrant deeper examination regarding their applicability, scalability, and risk management in manufacturing contexts. Finally, future research should emphasize ecosystem-level innovation, analyzing how AI-enabled collaboration among suppliers, manufacturers, and customers reshapes value chains and business models. Overall, advancing methodological rigor, contextual diversity, sustainability integration, and ethical governance considerations will be critical for developing a holistic understanding of AI-driven innovation in next-generation manufacturing systems.

Conclusion

In conclusion, AI-driven innovation in manufacturing industries represents a transformative paradigm that extends beyond mere automation to encompass intelligent, adaptive, and sustainable production systems. The integration of advanced AI technologies—such as machine learning, deep learning, computer vision, predictive analytics, digital twins, and Industrial Internet of Things (IIoT) applications—enables manufacturers to enhance operational efficiency, reduce costs, improve product quality, and achieve greater flexibility in production processes. Beyond operational benefits, AI serves as a strategic enabler, fostering business model innovation, servitization, and eco-efficient practices that align economic performance with environmental sustainability. The literature emphasizes that successful adoption of AI-driven innovation is contingent upon a combination of technological readiness, organizational capabilities, workforce skills, leadership commitment, and alignment with environmental and market pressures. At the same time, challenges such as data complexity, cybersecurity risks, high implementation costs, ethical considerations, and regulatory compliance require careful managerial attention and structured governance frameworks. From a theoretical perspective, frameworks such as Resource-Based View (RBV), Dynamic Capabilities, and socio-technical systems theory provide valuable lenses for understanding how AI capabilities are developed, deployed, and leveraged for competitive advantage. Looking forward, future research should explore longitudinal impacts, human–AI collaboration, sustainability integration, and ecosystem-level innovation to provide more holistic insights into AI-driven manufacturing transformation. Ultimately, AI-driven innovation positions manufacturing industries at the forefront of Industry 4.0 and green industrialization, enabling firms to achieve resilient, intelligent, and sustainable production systems that can adapt to evolving technological, environmental, and market demands.

References

1. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108
2. Bocken, N. M. P., Short, S. W., Rana, P., & Evans, S. (2014). A literature and practice review to develop sustainable business model archetypes. Journal of Cleaner Production, 65, 42–56. https://doi.org/10.1016/j.jclepro.2013.11.039
3. Chen, Y. S., Lai, S. B., & Wen, C. T. (2006). The influence of green innovation performance on corporate advantage in Taiwan. Journal of Business Ethics, 67(4), 331–339. https://doi.org/10.1007/s10551-006-9025-5
4. DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101
5. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data. International Journal of Information Management, 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021
6. Elkington, J. (1997). Cannibals with forks: The triple bottom line of 21st century business. Capstone Publishing.
7. Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. Journal of Cleaner Production, 252, 119869. https://doi.org/10.1016/j.jclepro.2019.119869
8. Gupta, S., Chen, H., Hazen, B. T., Kaur, S., & Gonzalez, E. D. S. (2019). Circular economy and big data analytics: A stakeholder perspective. Technological Forecasting and Social Change, 144, 466–474. https://doi.org/10.1016/j.techfore.2018.06.030
9. Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework. International Journal of Production Research, 56(8), 2960–2975. https://doi.org/10.1080/00207543.2017.1403660
10. Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001
11. Li, L. (2018). China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0". Technological Forecasting and Social Change, 135, 66–74. https://doi.org/10.1016/j.techfore.2017.05.028
12. Liu, Y., & Atuahene-Gima, K. (2018). Enhancing product innovation performance in a dysfunctional competitive environment. Journal of Product Innovation Management, 35(6), 910–932. https://doi.org/10.1111/jpim.12461
13. Porter, M. E., & van der Linde, C. (1995). Green and competitive. Harvard Business Review, 73(5), 120–134.
14. Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.
15. Sharma, G. D., Talan, G., & Jain, M. (2021). Policy response to the COVID-19 pandemic and environmental sustainability. Journal of Cleaner Production, 292, 126042. https://doi.org/10.1016/j.jclepro.2021.126042
16. Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in Industry 4.0. Procedia CIRP, 40, 536–541. https://doi.org/10.1016/j.procir.2016.01.129
17. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006
18. Teece, D. J. (2007). Explicating dynamic capabilities. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

19. Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.
20. Zhang, Y., Ren, S., Liu, Y., & Si, S. (2017). A big data analytics architecture for cleaner manufacturing and maintenance processes. Journal of Cleaner Production, 142, 626–641. https://doi.org/10.1016/j.jclepro.2016.07.123.