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Artificial Intelligence-Based Predictive Maintenance and Energy Optimization in Smart Manufacturing: A Comparative Engineering Systems Study of Japan and Canada

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***Abstract* (English) (Book Antiqua, 12pt Bold) :**

This article examines how artificial intelligence-based predictive maintenance and energy optimization systems influence operational performance, engineering resilience, and sustainable industrial transformation in advanced smart manufacturing ecosystems. Using a comparative engineering systems analysis of Japan and Canada, the study investigates how different industrial structures, digital infrastructures, energy systems, and technology-governance models shape the implementation of AI-enabled manufacturing optimization. Japan represents a highly automated, robotics-intensive manufacturing ecosystem with strong cyber-physical integration in automotive, electronics, and precision machinery sectors. Canada represents a resource-integrated and sustainability-oriented industrial ecosystem where AI, industrial IoT, and energy optimization are increasingly applied across advanced manufacturing, mining equipment, aerospace, and clean-technology production. Drawing on OECD digital transformation evidence, International Energy Agency industrial energy-efficiency data, International Federation of Robotics indicators, World Economic Forum smart manufacturing reports, IEEE and Scopus-indexed engineering literature, and institutional technology-policy documents, the article demonstrates that AI-driven predictive maintenance improves system reliability, reduces operational downtime, enhances energy visibility, and supports sustainability-oriented production. However, the comparison also reveals that engineering outcomes depend on data interoperability, workforce capability, computational infrastructure, cybersecurity governance, and energy-system integration. The article contributes to engineering and applied science *scholarship by proposing a conceptual model linking AI-enabled sensing, predictive analytics, operational optimization, system resilience, and sustainable socio-technical development.*

Keywords : *Artificial intelligence; predictive maintenance; smart manufacturing; energy optimization; cyber-physical systems; industrial IoT; engineering resilience; sustainable manufacturing; Japan; Canada; digital transformation; applied engineering systems.*

Abstrak (Indonesia)

Artikel ini mengkaji bagaimana pemeliharaan prediktif berbasis kecerdasan buatan dan sistem optimasi energi memengaruhi kinerja operasional, ketahanan teknik, dan transformasi industri berkelanjutan dalam ekosistem manufaktur cerdas tingkat lanjut. Dengan menggunakan analisis sistem teknik komparatif Jepang dan Kanada, studi ini menyelidiki bagaimana struktur industri, infrastruktur digital, sistem energi, dan model tata kelola teknologi yang berbeda membentuk implementasi optimasi manufaktur yang didukung AI. Jepang mewakili ekosistem manufaktur yang sangat otomatis dan intensif robotika dengan integrasi siber-fisik yang kuat di sektor otomotif, elektronik, dan mesin presisi. Kanada mewakili ekosistem industri yang terintegrasi sumber daya dan berorientasi pada keberlanjutan di mana AI, IoT industri, dan optimasi energi semakin banyak diterapkan di seluruh manufaktur canggih, peralatan pertambangan, kedirgantaraan, dan produksi teknologi bersih. Dengan mengacu pada bukti transformasi digital OECD, data efisiensi energi industri Badan Energi Internasional, indikator Federasi Robotika Internasional, laporan manufaktur cerdas Forum Ekonomi Dunia, literatur teknik yang diindeks IEEE dan Scopus, dan dokumen kebijakan teknologi institusional, artikel ini menunjukkan bahwa pemeliharaan prediktif yang didorong AI meningkatkan keandalan sistem, mengurangi waktu henti operasional, meningkatkan visibilitas energi, dan mendukung produksi yang berorientasi pada keberlanjutan. Namun, perbandingan ini juga mengungkapkan bahwa hasil rekayasa bergantung pada interoperabilitas data, kemampuan tenaga kerja, infrastruktur komputasi, tata kelola keamanan siber, dan integrasi sistem energi. Artikel ini berkontribusi pada kajian rekayasa dan ilmu terapan dengan mengusulkan model

konseptual yang menghubungkan penginderaan berbasis AI, analitik prediktif, optimasi operasional, ketahanan sistem, dan pembangunan sosial-teknis berkelanjutan.

Kata kunci : Kecerdasan buatan; pemeliharaan prediktif; manufaktur cerdas; optimasi energi; sistem siber-fisik; IoT industri; ketahanan rekayasa; manufaktur berkelanjutan; Jepang; Kanada; transformasi digital; sistem rekayasa terapan.

Introduction

Global manufacturing is undergoing a structural transformation driven by the convergence of artificial intelligence, cyber-physical systems, industrial robotics, cloud and edge computing, machine learning, digital twins, advanced sensing, and sustainability-oriented engineering governance. This transformation is not merely a matter of technological modernization; it redefines how industrial systems are designed, monitored, optimized, maintained, and governed. Manufacturing systems increasingly operate as data-intensive engineering environments in which production equipment, sensors, control algorithms, maintenance systems, energy infrastructures, and human operators interact continuously through digital platforms (Lee et al., 2015; Monostori et al., 2016). Within this context, AI-based predictive maintenance and energy optimization have become central mechanisms for linking engineering systems to technological implementation, operational performance, optimization outcomes, and sustainable socio-technical development.

The global industrial context underscores the importance of this issue. The industrial sector remains one of the largest consumers of energy and one of the most technically complex domains for sustainability transition. The International Energy Agency reports that industry accounts for approximately 37% of global final energy consumption, indicating that improvements in industrial energy performance are central to climate and resource-efficiency objectives (IEA, 2025). At the same time, industrial automation is accelerating. The International Federation of Robotics reports that global industrial robot installations reached 542,000 units in 2024, more than double the level recorded a decade earlier (IFR, 2025). These trends reveal a dual transformation: manufacturing is becoming more automated and more energy-constrained.

Consequently, the central engineering challenge is no longer simply how to produce more efficiently, but how to produce intelligently, reliably, adaptively, and sustainably.

AI-based predictive maintenance addresses this challenge by shifting maintenance logic from reactive repair and scheduled replacement toward data-driven anticipation of failure. Traditional maintenance systems often rely on periodic inspection, operator experience, or conservative replacement schedules. Such approaches may reduce failure risk but frequently generate unnecessary downtime, premature component replacement, and inefficient resource use. AI-enabled predictive maintenance integrates sensor data, equipment histories, vibration signals, thermal profiles, acoustic emissions, production loads, and environmental conditions to estimate failure probability and optimize maintenance timing (Carvalho et al., 2019; Zonta et al., 2020). In engineering terms, predictive maintenance converts physical degradation processes into computationally interpretable signals that support operational decision-making.

Energy optimization is similarly transformed by AI and industrial IoT systems. Conventional industrial energy management often relies on aggregate consumption monitoring, historical benchmarking, and static efficiency targets. AI-enabled energy optimization allows manufacturing systems to monitor machine-level energy demand, identify abnormal consumption patterns, simulate production schedules, optimize load distribution, and coordinate energy use with electricity prices or renewable-energy availability (Javaid et al., 2022). This is particularly significant in smart manufacturing environments where robotics, machine tools, heating systems, compressed air, data centers, and quality-control systems operate simultaneously. Energy performance therefore becomes a cyber-physical optimization problem rather than a purely managerial or infrastructural issue.

Japan and Canada provide analytically important comparative cases. Japan is one of the world's most advanced manufacturing economies, with strong capabilities in robotics, automotive engineering, electronics, precision machinery, and lean production systems. Its manufacturing ecosystem is characterized by high automation intensity, mature industrial engineering practices, advanced robotics integration, and strong quality-control traditions (IFR, 2025). Canada, by contrast, represents a technologically advanced but structurally different manufacturing ecosystem, shaped by aerospace, automotive, clean technology, natural-resource processing, advanced materials, and AI research capacity. Canada's industrial transformation is closely linked to sustainability, energy governance, resource efficiency, and the application of AI to industrial productivity and clean-technology development (OECD, 2023; World Bank, 2024).

The comparison is theoretically valuable because Japan and Canada differ in manufacturing density, robotics intensity, energy structure, industrial specialization, and digital governance. Japan's engineering model emphasizes production discipline, automation maturity, robotics integration, and incremental process improvement. Canada's model emphasizes AI research ecosystems, energy-resource integration, sustainability governance, and sectoral diversity. These differences allow the study to investigate how AI-based predictive maintenance and energy optimization perform under different socio-technical and industrial conditions.

Existing scholarship provides strong foundations but remains incomplete. Lee et al. (2015) conceptualized cyber-physical manufacturing systems as architectures that connect physical production assets with computational intelligence. Monostori et al. (2016) emphasized that cyber-physical production systems enable decentralized intelligence and adaptive manufacturing. Carvalho et al. (2019) demonstrated that machine learning improves predictive maintenance through classification, regression, anomaly detection, and fault diagnosis. Zonta et al. (2020) further showed that predictive maintenance is a core component of Industry 4.0 reliability. While these studies explain technical mechanisms, they often provide limited comparative interpretation of how national industrial structures mediate implementation outcomes.

Other studies emphasize sustainability and industrial digitalization. Javaid et al. (2022) argue that Industry 4.0 technologies can support environmental sustainability through energy monitoring, waste reduction, and resource optimization. Ivanov and Dolgui (2021) demonstrate that digital twins can enhance supply-chain resilience under disruption. Tao et al. (2019) show that digital twin systems enable full life-cycle optimization of industrial assets. However, current literature often separates predictive maintenance from energy optimization, even though both are operationally connected in real manufacturing systems. Equipment degradation may increase energy consumption;

inefficient scheduling may intensify machine wear; and poor maintenance may reduce both reliability and sustainability performance.

While previous studies emphasize AI capability, existing scholarship remains limited in explaining how predictive maintenance and energy optimization interact as integrated engineering functions. Other researchers argue that AI enhances industrial productivity, but current scholarship often fails to explain how data infrastructure, workforce skills, energy systems, and governance arrangements shape actual performance outcomes. Existing literature also remains limited in comparative engineering analysis. Many studies focus on single factories, single technologies, or single sectors, rather than comparing how different industrial ecosystems condition technological implementation.

This article addresses six research gaps. First, it addresses a theoretical gap by integrating predictive maintenance theory, energy-optimization engineering, cyber-physical systems analysis, and resilience engineering. Second, it addresses an empirical gap by using comparative evidence from two advanced industrial economies rather than relying on isolated technological cases. Third, it addresses a technological integration gap by analyzing predictive maintenance and energy optimization as mutually reinforcing engineering functions. Fourth, it addresses a comparative engineering gap by explaining how Japan and Canada differ in automation intensity, energy governance, industrial structure, and AI implementation pathways. Fifth, it addresses an operational gap by linking AI systems to downtime reduction, energy visibility, maintenance scheduling, and adaptive production. Sixth, it addresses a sustainability gap by evaluating how AI-enabled manufacturing contributes to resource efficiency and socio-technical resilience.

The novelty of this article lies in its comparative systems argument: AI-based predictive maintenance and energy optimization are not independent digital tools but coupled engineering capabilities whose effectiveness depends on cyber-physical integration, data interoperability, algorithmic reliability, human expertise, and sustainability governance. The article develops a causal framework in which sensorized engineering infrastructure enables data acquisition; AI analytics transforms data into predictive insight; predictive insight supports maintenance and energy optimization;

optimization improves operational resilience; and resilience contributes to sustainable socio-technical development.

The research objective of this study is to comparatively analyze how AI-based predictive maintenance and energy optimization systems influence operational performance, engineering resilience, and sustainability outcomes in the smart manufacturing ecosystems of Japan and Canada.

Metode

Bagian ini

This study adopts a comparative engineering systems analysis to examine the implementation and performance implications of AI-based predictive maintenance and energy optimization in Japan and Canada. The methodological design is aligned with cyber-physical systems theory, resilience engineering, industrial energy-systems analysis, and socio-technical innovation theory. Japan and Canada were selected through theoretically informed comparative logic because both are advanced economies with strong engineering capabilities, yet they represent structurally different manufacturing configurations. Japan provides a robotics-intensive, automation-mature, precision-oriented manufacturing case with strong integration in automotive, electronics, and machinery sectors. Canada provides a sustainability-oriented, resource-integrated, AI-capable industrial case in which advanced manufacturing intersects with aerospace, clean technology, mining equipment, energy systems, and industrial decarbonization. The comparative variables include automation intensity, predictive maintenance maturity, sensor and IoT integration, data interoperability, energy-monitoring capability, AI analytics adoption, workforce digital competence, cybersecurity governance, operational resilience, and sustainability performance. These variables were selected because they connect the research problem to engineering theory, comparative system architecture, technological implementation, industrial performance, and sustainability interpretation.

The empirical basis integrates institutional datasets, engineering reports, and peer-reviewed studies, including International Energy Agency industrial energy-efficiency data, International Federation of Robotics automation indicators, OECD digital transformation and AI policy evidence, World Economic Forum smart manufacturing reports, World Bank productivity and technology-transition analyses, IEEE and Scopus-indexed research on predictive maintenance, cyber-physical systems, digital twins, energy optimization, and sustainable manufacturing. Analytical interpretation combines comparative industrial systems evaluation with simulation-based reasoning derived from reported engineering mechanisms, including downtime reduction, anomaly detection, load optimization, equipment degradation modeling, energy-intensity improvement, and adaptive scheduling. Reliability was strengthened through triangulation across institutional reports, scholarly literature, and sectoral technology evidence. Validity was supported by matching each variable to observable engineering mechanisms rather than unsupported claims. Ethical and governance considerations include algorithmic transparency, industrial cybersecurity, workforce displacement risk, data sovereignty, computational energy demand, and the reliability of AI-driven operational decisions. The study is limited by cross-country differences in industrial classification, firm-level reporting, and digital maturity metrics; however, analytical consistency is maintained by focusing on causal engineering mechanisms and verifiable system-level evidence rather than fabricated laboratory measurements or respondent data.

Findings and Discussion

1. Comparative Architecture of Smart Manufacturing Systems

The comparison reveals that Japan and Canada possess distinct smart manufacturing architectures that shape the implementation of AI-based predictive maintenance and energy optimization. Japan's manufacturing ecosystem is characterized by high automation maturity, dense robotics integration, lean production traditions, and strong quality-control systems. In this environment, AI-based predictive maintenance is typically embedded into already disciplined production systems, where equipment utilization, process stability, and defect minimization are central engineering priorities. Predictive analytics therefore functions as an extension of Japan's long-standing emphasis on reliability, continuous improvement, and precision manufacturing.

Canada's smart manufacturing architecture is more heterogeneous. Its manufacturing ecosystem includes aerospace, automotive components, clean technology, food processing, industrial machinery, mining equipment, and advanced materials. AI deployment is strongly supported by research universities, national AI institutes, and industrial innovation programs, but manufacturing digitalization varies more significantly across sectors and regions. Predictive maintenance in Canada is therefore often implemented selectively in high-value industrial systems where asset reliability, remote monitoring, energy efficiency, and safety are critical. This includes aerospace production, resource-processing equipment, industrial energy systems, and advanced manufacturing facilities.

The findings indicate that Japan's advantage lies in operational standardization and automation depth, while Canada's advantage lies in AI research capability, energy-system integration, and sustainability-oriented innovation. Japan's manufacturing systems are generally better positioned for high-frequency machine data capture because robotics and automated production lines are already deeply embedded. Canada's systems are better positioned for cross-sector AI experimentation and energy-optimization models because industrial sustainability and resource efficiency are central policy and economic concerns.

This comparison demonstrates that AI implementation depends on prior engineering infrastructure. Where sensors, robotics, and standardized production routines are already mature, predictive maintenance can be integrated more rapidly into production control. Where manufacturing systems are more diverse, predictive maintenance requires greater customization but may generate broader sustainability benefits across energy-intensive and resource-linked sectors. This finding supports cyber-physical systems theory, which argues that intelligent manufacturing depends on the integration of physical processes, computational systems, and organizational decision structures (Lee et al., 2015; Monostori et al., 2016).

2. Predictive Maintenance, Reliability Engineering, and Operational Performance

The findings indicate that AI-based predictive maintenance improves operational performance by reducing unplanned downtime, improving equipment availability, and increasing maintenance precision. In Japan, predictive maintenance is especially relevant to automotive production, robotics-intensive assembly lines, electronics manufacturing, and precision machinery. Equipment failure in these sectors can disrupt tightly synchronized production flows. AI models using vibration analysis, thermal monitoring, acoustic signals, and process-control data enable earlier detection of mechanical degradation and operational anomalies. This strengthens reliability-centered maintenance and supports production continuity.

In Canada, predictive maintenance is particularly significant in asset-intensive and geographically dispersed industries. Aerospace manufacturing, industrial machinery, mining equipment, and energy-linked manufacturing systems often involve high-value assets where failure can generate significant economic and safety consequences. AI-enabled monitoring allows firms to detect early-stage degradation in rotating equipment, hydraulic systems, robotics, and thermal processes. Because Canadian industrial systems often operate across larger geographic and sectoral variation, remote monitoring and cloud-based maintenance analytics are especially valuable.

The cross-case comparison shows that Japan's predictive maintenance model is production-line intensive, while Canada's model is asset-reliability intensive. Japan emphasizes continuous operation within highly synchronized manufacturing environments. Canada emphasizes reliability, safety, and energy performance across varied industrial assets. Both models demonstrate that predictive maintenance is not merely a data-science application but an engineering control function that links material degradation, sensor systems, machine learning, maintenance planning, and operational decision-making.

The findings are consistent with Carvalho et al. (2019) and Zonta et al. (2020), who show that machine learning improves fault diagnosis and maintenance prediction. However, this article extends that literature by demonstrating that predictive maintenance outcomes depend on system architecture. High automation density improves data availability, but sectoral diversity creates opportunities for broader AI adaptation. The engineering implication is that predictive maintenance systems should be designed according to operational context, asset criticality, sensor quality, and maintenance-response capability.

3. Energy Optimization, Sustainability Engineering, and Industrial Efficiency

Energy optimization represents a second major mechanism through which AI-enabled smart manufacturing supports sustainability. In Japan, energy optimization is shaped by high industrial energy costs, limited domestic energy resources, and a long-standing focus on efficiency. AI-enabled systems help manufacturers monitor electricity use across robotics, machine tools, thermal systems, compressed air, and factory utilities. By integrating energy data with production schedules, Japanese manufacturers can reduce peak loads, identify inefficient machines, and coordinate equipment use with operational demand.

In Canada, energy optimization is shaped by a different industrial context. Canada has significant energy resources, but industrial decarbonization, clean technology, and emissions reduction remain major policy and engineering priorities. AI-based energy optimization is therefore closely connected to sustainability governance, electrification, renewable energy integration, and resource-processing efficiency. Canadian manufacturing facilities can use AI models to optimize heating, cooling, motor systems, process loads, and energy storage coordination. In energy-intensive sectors, these systems support both cost reduction and carbon-management objectives.

The comparison reveals that energy optimization has different strategic meanings in each case. In Japan, it primarily strengthens operational efficiency and energy security within dense manufacturing environments. In Canada, it supports sustainability transition, resource productivity, and industrial decarbonization. This difference demonstrates that AI-enabled energy optimization is shaped by national energy systems and policy priorities.

The evidence suggests that predictive maintenance and energy optimization are technically interdependent. Degraded equipment often consumes more energy, generates more heat, produces more vibration, and increases defect risk. AI systems that integrate maintenance data with energy data can identify hidden inefficiencies that would not be visible through separate monitoring systems. For example, an electric motor may continue operating within acceptable production limits while consuming abnormal energy due to bearing wear. A combined predictive-maintenance and energy-optimization system can detect this condition earlier than either maintenance or energy monitoring alone.

This finding contributes to sustainability engineering scholarship by demonstrating that energy efficiency should be treated as an operationally embedded engineering problem rather than a separate environmental objective. It also extends Industry 4.0 sustainability literature by showing that AI contributes to sustainability most effectively when it integrates equipment health, production scheduling, resource use, and energy-system behavior.

4. Workforce Capability, Human–Machine Interaction, and Socio-Technical Adaptation

The findings demonstrate that workforce capability is a decisive factor in the performance of AI-based predictive maintenance and energy optimization systems. Japan possesses strong manufacturing discipline, technical training traditions, and operator knowledge embedded in lean production systems. This supports the integration of AI tools into existing operational routines. However, Japan also faces demographic constraints, including workforce aging and potential shortages of digital engineering talent. AI systems may reduce some labor burdens, but they also require engineers capable of interpreting predictive models, validating anomalies, and managing human-machine interfaces.

Canada has strong AI research capability and a highly educated engineering workforce, particularly in major innovation regions. However, manufacturing digitalization is uneven across sectors and firm sizes. Large aerospace, automotive, and clean-technology firms may possess advanced data capability, while smaller manufacturers may lack the resources to implement full predictive analytics systems. This creates a socio-technical divide between digitally mature firms and firms still dependent on conventional maintenance and energy-management practices.

The comparison indicates that AI-enabled manufacturing transformation requires both technical infrastructure and organizational learning. Predictive algorithms may identify failure risk, but maintenance teams must trust, interpret, and act on the prediction. Energy-optimization systems may recommend scheduling changes, but production managers must balance energy savings against delivery deadlines, quality constraints, and workforce availability. Human-machine interaction is therefore not peripheral; it is central to implementation success.

This finding aligns with socio-technical systems theory, which emphasizes that technological systems and organizational structures co-evolve (Geels, 2004). It also supports resilience engineering, which argues that adaptive capacity depends on the ability of human and technical systems to monitor, respond, learn, and anticipate (Hollnagel, 2014). AI systems improve anticipation, but human expertise remains essential for contextual judgment and accountability.

5. Cybersecurity, Data Governance, and Engineering Resilience

AI-based predictive maintenance and energy optimization increase the connectivity of manufacturing systems, but they also introduce cybersecurity and data-governance risks. Sensor networks, cloud platforms, edge devices, industrial control systems, and AI models create expanded attack surfaces. If data streams are manipulated, predictive maintenance models may generate false alerts or fail to detect equipment degradation. If energy-optimization systems are compromised, production scheduling and load management may be disrupted. Engineering resilience therefore requires secure data infrastructure.

Japan's highly integrated production environments benefit from strong process discipline but may face risks associated with interconnected robotics and industrial control systems. Canada's distributed industrial structure creates different risks, especially where remote monitoring and cloud analytics are used across geographically dispersed assets. In both cases, cybersecurity becomes an engineering performance issue rather than merely an information-technology concern.

The comparison demonstrates that resilience depends on the ability to maintain safe and reliable function under cyber, operational, environmental, and supply-chain disruption. AI-based systems can improve resilience by detecting anomalies and simulating risks, but they can also create dependency on data availability and algorithmic reliability. This dual character requires governance mechanisms including model validation, secure data protocols, explainable AI, redundancy planning, and human override capability.

This finding contributes to engineering governance scholarship by showing that AI-enabled optimization must be evaluated through reliability, safety, transparency, and accountability. Smart manufacturing systems are not sustainable if they are efficient but fragile. Long-term industrial resilience requires trustworthy AI, secure cyber-physical infrastructure, and institutional capacity to govern technological complexity.

Table 1. Analytical Matrix of Comparative Engineering and Applied Science Systems

Variable	Japan	Canada	Empirical/Simulation Evidence	Analytical Interpretation
Industrial structure	Robotics-intensive manufacturing in automotive, electronics, and precision machinery	Sectorally diverse manufacturing linked to aerospace, clean technology, resources, and advanced materials	IFR, OECD, and WEF reports identify both as advanced industrial economies with different automation profiles	Industrial specialization shapes AI implementation pathways
Predictive maintenance model	Production-line reliability and synchronized equipment monitoring	Asset-reliability monitoring across diverse and often distributed industrial systems	Predictive maintenance literature shows AI improves fault detection and maintenance scheduling	Japan optimizes continuity; Canada optimizes asset reliability and safety
Energy optimization priority	Energy security, efficiency, peak-load reduction, and machine-level monitoring	Decarbonization, resource efficiency, electrification, and clean-technology integration	IEA industrial energy data demonstrate the importance of energy efficiency in manufacturing	Energy-system context determines sustainability strategy

Cyber-physical integration	Strong integration through robotics and lean production systems	Uneven but growing integration through AI, IoT, and advanced manufacturing programs	CPS literature emphasizes the role of sensing, computation, and control	Japan has deeper production integration; Canada has broader cross-sector experimentation
Workforce capability	Strong manufacturing expertise but demographic and digital-talent pressures	Strong AI research capacity but uneven SME digital readiness	OECD evidence highlights AI adoption divides across firms and regions	Human capability mediates technological value
Operational performance	High reliability, quality control, and equipment synchronization	Flexible optimization across sectors and asset types	Engineering studies show AI improves downtime reduction and anomaly detection	Performance depends on fit between AI system and industrial context
Sustainability outcomes	Efficiency gains through disciplined manufacturing and energy monitoring	Sustainability gains through energy optimization and clean-industrial transition	IEA and WEF reports link digitalization with industrial sustainability potential	Sustainability depends on integration between AI and energy governance
Governance challenge	Maintaining digital capability under workforce aging and cyber-physical complexity	Reducing adoption gaps across sectors and firm sizes	OECD reports identify uneven AI adoption as a policy concern	Governance determines whether AI benefits scale systemically

The analytical matrix demonstrates that Japan and Canada represent different but complementary smart manufacturing pathways. Japan's strengths are automation maturity, production discipline, robotics integration, and reliability engineering. Canada's strengths are AI research capacity, sustainability orientation, energy-resource integration, and cross-sector experimentation. The comparison reveals that AI-based predictive maintenance and energy optimization are most effective when technological systems are aligned with industrial structure, energy context, workforce capability, and governance architecture.

The deeper analytical implication is that smart manufacturing performance is generated through system alignment rather than technology adoption alone. AI models require high-quality data; sensors require reliable physical integration; predictions require human interpretation; optimization requires organizational authority; and sustainability requires energy-system coordination. Without this alignment, AI systems may remain technically impressive but operationally limited. With alignment, predictive maintenance and energy optimization become core mechanisms of engineering resilience and sustainable industrial development.

Conceptual Model: AI-Enabled Predictive Maintenance and Sustainable Manufacturing Optimization

This article proposes the following conceptual engineering model:

Sensorized Engineering Infrastructure → AI Predictive Analytics → Maintenance and Energy Optimization → Operational Resilience → Sustainable Socio-Technical Development

Sensorized engineering infrastructure represents the foundation of intelligent manufacturing. It includes industrial IoT sensors, machine controllers, robotics systems, energy meters, production databases, and digital platforms. These systems generate the operational data required for AI analysis.

AI predictive analytics transforms industrial data into engineering insight. Machine learning models identify degradation patterns, abnormal energy use, process instability, and production risks. Predictive analytics therefore mediates the relationship between digital infrastructure and operational decision-making.

Maintenance and energy optimization represent the applied engineering outcome. Predictive maintenance reduces downtime and improves asset reliability, while energy optimization reduces waste and improves resource efficiency. When integrated, these functions allow manufacturers to detect equipment conditions that simultaneously threaten reliability and sustainability.

Operational resilience emerges when manufacturing systems can anticipate, absorb, adapt to, and recover from disruption. AI systems strengthen resilience by improving monitoring and anticipation, but resilience also depends on human expertise, cybersecurity, governance, and organizational learning.

Sustainable socio-technical development is the final outcome. It refers to manufacturing systems that improve productivity while reducing waste, lowering energy intensity, supporting workforce adaptation, and strengthening technological governance. The model demonstrates that sustainable manufacturing is not achieved by automation alone but by the integration of engineering systems, AI analytics, operational practice, and socio-technical governance.

Conclusion

This study examined how AI-based predictive maintenance and energy optimization systems influence operational performance, engineering resilience, and sustainability outcomes in the smart manufacturing ecosystems of Japan and Canada. The findings demonstrate that AI-enabled manufacturing systems improve operational performance by enhancing equipment monitoring, failure prediction, maintenance scheduling, energy visibility, and adaptive production control. However, the comparison also shows that technological outcomes depend on industrial structure, data interoperability, workforce capability, cybersecurity governance, and energy-system integration.

The main analytical finding is that Japan and Canada represent two different pathways of intelligent manufacturing transformation. Japan’s pathway is characterized by robotics-intensive production, strong process discipline, lean manufacturing traditions, and high equipment synchronization. This creates favorable conditions for AI-based predictive maintenance in production-line environments. Canada’s pathway is characterized by sectoral diversity, AI research strength, sustainability orientation, and energy-resource integration. This creates favorable conditions for AI-enabled energy optimization and asset-reliability management across varied industrial contexts.

The theoretical contribution of this article lies in integrating predictive maintenance, energy optimization, cyber-physical systems theory, and resilience engineering within a comparative applied-science framework. The study demonstrates that predictive maintenance and energy optimization should be understood as coupled engineering capabilities rather than separate technical applications. Equipment health, energy efficiency, production quality, and sustainability performance are operationally interconnected.

The empirical and technological contribution lies in explaining how institutional reports, robotics indicators, energy-efficiency evidence, and engineering literature can be interpreted through a comparative systems framework. The findings indicate that AI contributes to sustainable manufacturing not merely by increasing automation, but by improving the capacity of industrial systems to anticipate failure, optimize energy use, adapt to constraints, and maintain reliable performance.

The industrial implications are significant. Manufacturers should design AI systems around operational problems rather than technological novelty. Predictive maintenance should be integrated with energy monitoring, production scheduling, quality control, and human decision-making. Energy optimization should account for equipment degradation, process variability, and computational energy demand. Firms should also invest in workforce training, cybersecurity, model validation, and data governance.

The policy implications are equally important. Governments should support industrial AI adoption through interoperability standards, digital skills programs, secure industrial data infrastructure, clean-energy integration, and targeted support for small and medium-sized manufacturers. Sustainability policy should recognize that AI-enabled manufacturing can reduce waste and energy use, but only when computational infrastructure is governed responsibly.

The study has limitations. It relies on secondary evidence and comparative systems interpretation rather than plant-level experimental measurement. Cross-national differences in industrial classification and reporting standards limit direct quantitative comparison. Future research should conduct longitudinal plant-level studies, develop predictive-maintenance maturity indices, measure the energy footprint of industrial AI systems, and evaluate hybrid models combining Japan's production discipline with Canada's sustainability-oriented AI ecosystem.

Overall, this article concludes that AI-based predictive maintenance and energy optimization are critical engineering mechanisms for sustainable smart manufacturing. Their value depends not only on algorithmic performance but also on cyber-physical integration, human expertise, energy governance, and socio-technical resilience.

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