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Edge AI, Industrial IoT, and Autonomous Control for Sustainable Predictive Manufacturing: A Comparative Engineering Systems Analysis of the United States and Taiwan

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Abstract **(English)**
This article investigates how edge artificial intelligence, Industrial Internet of Things architectures, and autonomous control systems influence predictive manufacturing, operational optimization, engineering resilience, and sustainability outcomes in advanced industrial ecosystems. Using a comparative engineering systems analysis of the United States and Taiwan, the study examines two technologically advanced yet structurally different industrial cases: the United States as a large-scale, diversified, AI-intensive manufacturing and digital infrastructure ecosystem, and Taiwan as a highly specialized, semiconductor-centered, precision manufacturing system with dense cyber-physical integration. The study draws on engineering literature, industrial automation indicators, OECD digital transformation evidence, International Energy Agency energy-efficiency data, International Federation of Robotics reports, World Economic Forum smart manufacturing analyses, and IEEE-indexed studies on edge computing, industrial IoT, predictive maintenance, and autonomous manufacturing control. The findings demonstrate that edge AI reduces decision latency, improves predictive maintenance responsiveness, enhances quality-control precision, and supports energy-aware production when integrated with robust industrial data infrastructure. However, the comparison reveals that technological performance depends on system architecture, semiconductor supply-chain integration, interoperability standards, cybersecurity governance, workforce capability, and sustainability alignment. This article contributes to engineering and applied science scholarship by proposing an integrated framework linking sensorized manufacturing infrastructure, edge AI analytics, autonomous

control, operational optimization, engineering resilience, and sustainable socio-technical industrial development.

Keywords
Edge artificial intelligence; Industrial Internet of Things; autonomous control; smart manufacturing; predictive maintenance; semiconductor manufacturing; sustainable engineering; cyber-physical systems; industrial optimization; engineering resilience; United States; Taiwan.

Abstrak (Indonesia)

Artikel ini meneliti bagaimana kecerdasan buatan (AI) di tepi jaringan (edge computing), arsitektur Industrial Internet of Things (IIoT), dan sistem kendali otonom memengaruhi manufaktur prediktif, optimasi operasional, ketahanan teknik, dan hasil keberlanjutan dalam ekosistem industri maju. Menggunakan analisis sistem rekayasa komparatif antara Amerika Serikat dan Taiwan, studi ini mengkaji dua kasus industri yang maju secara teknologi namun berbeda secara struktural: Amerika Serikat sebagai ekosistem manufaktur dan infrastruktur digital yang besar, terdiversifikasi, dan intensif AI, dan Taiwan sebagai sistem manufaktur presisi yang sangat terspesialisasi, berpusat pada semikonduktor, dengan integrasi siber-fisik yang padat. Studi ini mengacu pada literatur teknik, indikator otomatisasi industri, bukti transformasi digital OECD, data efisiensi energi Badan Energi Internasional, laporan Federasi Robotika Internasional, analisis manufaktur cerdas Forum Ekonomi Dunia, dan studi yang diindeks IEEE tentang komputasi tepi, IoT industri, pemeliharaan prediktif, dan kendali manufaktur otonom. Temuan menunjukkan bahwa AI di tepi jaringan mengurangi latensi pengambilan keputusan, meningkatkan respons pemeliharaan prediktif, meningkatkan presisi kontrol kualitas, dan mendukung produksi yang hemat energi ketika diintegrasikan dengan infrastruktur data industri yang kuat. Namun, perbandingan tersebut mengungkapkan bahwa kinerja teknologi bergantung pada arsitektur sistem, integrasi rantai pasokan semikonduktor, standar interoperabilitas, tata kelola keamanan siber, kemampuan tenaga kerja, dan keselarasan keberlanjutan. Artikel ini berkontribusi pada kajian teknik dan ilmu terapan dengan mengusulkan kerangka kerja terintegrasi yang menghubungkan infrastruktur manufaktur yang dilengkapi sensor, analitik AI di tepi

jaringan, kontrol otonom, optimasi operasional, ketahanan teknik, dan pengembangan industri sosio-teknis yang berkelanjutan.

Kata kunci : Kecerdasan buatan di tepi jaringan; Internet of Things Industri; kontrol otonom; manufaktur cerdas; pemeliharaan prediktif; manufaktur semikonduktor; teknik berkelanjutan; sistem siber-fisik; optimasi industri; ketahanan teknik; Amerika Serikat; Taiwan.

Introduction

Advanced manufacturing is increasingly shaped by the convergence of edge artificial intelligence, Industrial Internet of Things systems, autonomous control, robotics, digital twins, cyber-physical production systems, and sustainability-oriented engineering governance. This transformation reflects a fundamental shift in industrial engineering: manufacturing performance is no longer determined only by machine capability, production scale, or labor productivity, but increasingly by the ability of industrial systems to sense, compute, predict, decide, and adapt in real time. Manufacturing systems are becoming distributed computational environments in which machines, sensors, controllers, cloud platforms, edge devices, operators, and energy systems form interconnected socio-technical architectures (Lee et al., 2015; Monostori et al., 2016).

The global industrial context intensifies the significance of this transformation. Industrial systems remain among the largest consumers of global energy, and recent International Energy Agency evidence indicates that industry accounts for the largest share of global final energy demand, approaching 40% in 2024 (IEA, 2025). At the same time, automation continues to expand rapidly. The International Federation of Robotics reports that 542,000 industrial robots were installed worldwide in 2024, with annual installations exceeding 500,000 units for the fourth consecutive year (IFR, 2025). These trends indicate that modern industrial systems are becoming simultaneously more automated, more energy-intensive, more data-dependent, and more strategically important for sustainable development.

Edge AI has emerged as a critical engineering response to the limitations of cloud-dependent industrial analytics. In conventional cloud-based manufacturing systems, sensor data are transmitted to centralized platforms for processing and decision support. While this architecture supports large-scale analytics, it may introduce latency, bandwidth constraints, cybersecurity exposure, and reliability risks. Edge AI addresses these limitations by performing computational inference closer to machines, sensors, robots, and production assets. In manufacturing, this enables low-latency anomaly detection, real-time quality inspection, adaptive control, predictive maintenance, and energy optimization (Shi et al., 2016; Deng et al., 2020). The engineering importance of edge AI lies in its ability to transform industrial devices from passive data sources into intelligent operational nodes.

Industrial IoT systems provide the sensory and communication foundation for this transformation. Industrial IoT connects machines, programmable logic controllers, sensors, actuators, robotics systems, energy meters, and manufacturing execution systems through networked data infrastructures. When combined with AI, these systems support predictive maintenance, quality analytics, equipment health monitoring, digital twin synchronization, and autonomous process control (Atzori et al., 2017; Lu, 2017). However, the operational value of Industrial IoT depends on interoperability, data quality, cybersecurity, and integration with organizational decision systems. Fragmented sensor networks or poorly governed data platforms may produce large volumes of data without meaningful optimization.

Autonomous control represents the next stage of manufacturing intelligence. Whereas predictive analytics identifies likely future states, autonomous control enables systems to adjust operational parameters without continuous human intervention. In advanced manufacturing environments, autonomous control can regulate machine speed, tool wear compensation, thermal conditions, robotic trajectories, production scheduling, and energy consumption. This does not eliminate human engineering expertise; rather, it changes the role of engineers from manual process adjustment toward system supervision, model validation, exception management, and strategic optimization (Hollnagel, 2014; Tao et al., 2019).

The scientific and industrial problem addressed in this article is that intelligent manufacturing systems do not generate uniform outcomes across industrial ecosystems. Edge AI, Industrial IoT, and autonomous control are often presented as broadly applicable technologies, but their performance depends on national industrial structure, semiconductor supply-chain capacity, digital infrastructure, workforce capability, energy-system integration, cybersecurity governance, and innovation policy. This problem is theoretically important because it challenges technological determinism in engineering innovation. It is industrially important because firms and governments increasingly invest in AI-enabled manufacturing without sufficient understanding of the system conditions required for operational and sustainability gains.

The United States and Taiwan provide a particularly significant comparative context. The United States represents a large, diversified, AI-intensive industrial ecosystem with strengths in software, cloud computing, advanced manufacturing research, aerospace, automotive systems, defense manufacturing, energy technology, and semiconductor design. Its manufacturing transformation is shaped by distributed innovation networks, private-sector technology platforms, federal industrial policy, and growing investment in domestic semiconductor and advanced manufacturing capacity (OECD, 2023; World Bank, 2024). Taiwan, by contrast, represents a highly specialized, export-oriented, semiconductor-centered manufacturing ecosystem characterized by dense precision engineering, high process control, advanced electronics production, and globally strategic supply-chain integration. Taiwan's industrial system demonstrates how cyber-physical manufacturing, extreme quality control, and high-volume precision production can be integrated within a compact technological ecosystem.

The comparison is analytically valuable because the United States and Taiwan differ in industrial scale, specialization, governance structure, and manufacturing architecture. The United States offers broad technological diversity and strong AI research capacity, but its manufacturing digitalization is uneven across sectors and firm sizes. Taiwan offers exceptional specialization in semiconductor and electronics manufacturing, where process control, defect reduction, and equipment reliability are critical, but its industrial resilience is highly exposed to supply-chain concentration, energy security, and geopolitical risk. These differences make the comparison useful for explaining how engineering systems shape implementation outcomes.

Existing scholarship provides important but incomplete foundations. Lee et al. (2015) developed a cyber-physical architecture for Industry 4.0 manufacturing, emphasizing intelligent connectivity and data-driven decision-making. Monostori et al. (2016) explained how cyber-physical production systems enable decentralized manufacturing intelligence. Tao et al. (2019) demonstrated that digital twins support lifecycle optimization and real-time industrial coordination. While these studies clarify the technical architecture of smart manufacturing, they provide limited explanation of how edge AI and autonomous control perform differently across specialized and diversified industrial ecosystems.

Predictive maintenance literature further demonstrates the value of machine learning in industrial reliability. Carvalho et al. (2019) reviewed machine learning methods for predictive maintenance, showing how classification, regression, and anomaly detection improve maintenance planning. Zonta et al. (2020) showed that predictive maintenance is a core Industry 4.0 application, particularly for reducing downtime and improving asset utilization. However, current literature often underemphasizes the specific role of edge computing in reducing latency and enabling real-time maintenance decisions at machine level.

Sustainability-oriented manufacturing research has similarly advanced but remains fragmented. Bonilla et al. (2018) argued that Industry 4.0 can contribute to sustainability, although it may introduce new energy and resource challenges. Javaid et al. (2022) emphasized that digital manufacturing technologies can improve environmental outcomes through monitoring, waste reduction, and resource efficiency. Ivanov and Dolgui (2021) highlighted the role of digital twins in supply-chain resilience. However, existing scholarship rarely integrates edge AI, industrial IoT, autonomous control, predictive maintenance, and energy efficiency within a comparative engineering framework.

While previous studies emphasize smart manufacturing, current scholarship fails to sufficiently explain how computational location affects operational performance. Cloud computing, edge computing, and hybrid architectures differ in latency, bandwidth, security exposure, scalability, and resilience. Other researchers argue that AI improves industrial optimization, yet much of the literature insufficiently distinguishes between centralized analytics and edge-based autonomous control. Existing literature also remains limited in comparing large diversified industrial economies with highly specialized precision manufacturing ecosystems. Consequently, important theoretical, empirical, comparative, implementation, technological integration, and sustainability gaps remain.

The theoretical gap concerns the need to integrate cyber-physical systems theory, edge intelligence, resilience engineering, and sustainability engineering. The empirical gap concerns the limited comparative evidence explaining how AI-enabled manufacturing differs across industrial ecosystems. The comparative engineering gap concerns the lack of analysis between diversified and specialized manufacturing systems. The implementation gap concerns the limited understanding of how firms translate edge AI capability into operational control. The technological integration gap concerns the fragmented treatment of Industrial IoT, predictive maintenance, autonomous control, and energy optimization. The sustainability gap concerns the need to evaluate both efficiency gains and the energy demands of intelligent digital infrastructure.

The novelty of this article lies in conceptualizing edge AI not merely as a computational technology but as an engineering coordination mechanism that changes the spatial organization of industrial intelligence. By moving analytics closer to production assets, edge AI can reduce decision latency, improve local autonomy, strengthen resilience, and support energy-aware optimization. However, its effectiveness depends on interoperability, cybersecurity, workforce capability, and governance architecture. The article therefore contributes to engineering and applied science scholarship by developing a comparative systems framework linking sensorized infrastructure, edge analytics, autonomous control, operational optimization, resilience, and sustainable socio-technical development.

The analytical framework guiding this study proposes the following causal sequence: sensorized industrial infrastructure enables real-time data acquisition; edge AI transforms data into low-latency predictive intelligence; autonomous control translates predictive intelligence into operational adjustment; optimization improves reliability, quality, energy efficiency, and productivity; resilience emerges through adaptive system response; and sustainable socio-technical development occurs when operational intelligence is aligned with governance, workforce adaptation, cybersecurity, and environmental objectives.

The research objective of this study is to comparatively analyze how edge AI, Industrial IoT, and autonomous control systems influence predictive manufacturing performance, operational optimization, engineering resilience, and sustainability outcomes in the industrial ecosystems of the United States and Taiwan.

Method

Bagian ini

This study employs a comparative engineering systems analysis to examine how edge AI, Industrial IoT, and autonomous control influence predictive manufacturing and sustainable industrial performance in the United States and Taiwan. The research design is grounded in cyber-physical systems theory, resilience engineering, edge computing architecture, industrial IoT systems analysis, and sustainability engineering. The United States and Taiwan were selected through theoretically informed comparative logic because both occupy strategically significant positions in advanced manufacturing and semiconductor-linked technological systems, yet they differ sharply in industrial structure, manufacturing specialization, scale, governance coordination, and operational architecture. The United States represents a diversified AI-intensive manufacturing ecosystem with strengths in software platforms, aerospace, automotive systems, energy technologies, robotics research, semiconductor design, and advanced manufacturing policy. Taiwan represents a specialized precision manufacturing ecosystem centered on semiconductors, electronics, high-yield production, and dense cyber-physical process control. Comparative variables include edge AI maturity, Industrial IoT integration, autonomous control capability, predictive maintenance performance, quality-control precision, data interoperability, cybersecurity resilience, workforce digital capability, energy-efficiency integration, and sustainability governance.

The empirical basis integrates secondary datasets, institutional reports, and peer-reviewed engineering research, including International Energy Agency industrial energy-efficiency evidence, International Federation of Robotics automation indicators, OECD digital transformation and AI adoption reports, World Economic Forum smart manufacturing and Global Lighthouse Network analyses, World Bank productivity and technology-transition evidence, IEEE and Scopus-indexed literature on edge computing, Industrial IoT, predictive maintenance, cyber-physical systems, autonomous control, digital twins, semiconductor manufacturing, and sustainable manufacturing. Analytical interpretation combines comparative industrial systems evaluation with simulation-based engineering reasoning by examining reported mechanisms such as latency reduction, anomaly detection, quality inspection, equipment-health monitoring, energy-aware scheduling, process-control adaptation, and cyber-physical resilience. Reliability is strengthened through triangulation across institutional datasets, scholarly literature, and sectoral technology reports. Validity is supported by linking variables to observable engineering mechanisms rather than unsupported experimental claims. Ethical and governance considerations include industrial data sovereignty, cybersecurity, model reliability, algorithmic accountability, workforce displacement risk, semiconductor supply-chain vulnerability, and computational energy demand. The study is limited by cross-national differences in reporting systems, firm-level confidentiality, and the absence of uniform edge AI maturity metrics; however, analytical consistency is maintained by focusing on causal mechanisms connecting engineering systems, technological implementation, operational performance, optimization outcomes, and sustainable socio-technical development.

Findings and Discussion

1. Edge AI Architecture and the Spatial Distribution of Manufacturing Intelligence

The first major finding is that edge AI changes the spatial organization of manufacturing intelligence by relocating computational inference from centralized cloud systems toward production assets, machines, robots, sensors, and controllers. This architectural shift is especially significant in manufacturing environments where milliseconds of latency can affect quality, safety, throughput, or equipment integrity. The United States and Taiwan both deploy AI-enabled industrial systems, but their edge AI architectures reflect different industrial structures.

In the United States, edge AI adoption is distributed across multiple sectors, including aerospace manufacturing, automotive systems, energy equipment, robotics, medical devices, and semiconductor fabrication. This diversity creates opportunities for broad experimentation but also produces uneven maturity. Large firms and high-technology sectors increasingly integrate edge devices for anomaly detection, machine vision, and predictive maintenance, while smaller manufacturers may remain dependent on conventional automation or cloud-based analytics. The United States therefore demonstrates a heterogeneous edge AI ecosystem shaped by sectoral variation, firm size, digital infrastructure, and technology-platform availability.

Taiwan's edge AI architecture is more concentrated and operationally specialized. Semiconductor and electronics manufacturing require extremely low defect rates, stable process control, high equipment utilization, and rapid anomaly detection. Edge AI systems are particularly valuable in such environments because production data are generated at high frequency and must be processed with minimal delay. Machine vision, equipment telemetry, vibration analysis, temperature monitoring, and process-control signals can be analyzed at or near the production line to support rapid intervention. In Taiwan, the engineering logic of edge AI is therefore closely linked to yield optimization, equipment reliability, and precision process control.

The comparison reveals that edge AI creates different forms of value depending on manufacturing architecture. In the United States, edge AI supports flexibility across diverse industrial applications. In Taiwan, edge AI supports precision and reliability within specialized high-volume production systems. This finding extends edge computing literature by demonstrating that architecture cannot be evaluated only by technical metrics such as latency or bandwidth. It must also be interpreted through industrial context, asset criticality, product complexity, and operational risk.

Theoretically, this finding contributes to cyber-physical systems scholarship by showing that intelligence distribution is a core design choice in smart manufacturing. Lee et al. (2015) emphasized the importance of cyber-physical connectivity, but the present comparison demonstrates that where computation occurs is equally important. Edge AI enables local autonomy, while cloud systems support broader learning and coordination.

The optimal manufacturing architecture is therefore not purely centralized or decentralized but hybrid, combining edge responsiveness with cloud-scale optimization.

2. Predictive Maintenance, Industrial IoT, and Equipment Reliability

The second finding is that Industrial IoT-enabled predictive maintenance becomes substantially more operationally effective when combined with edge AI. Predictive maintenance depends on sensorized monitoring of equipment condition, including vibration, current, temperature, pressure, acoustic signals, tool wear, and process deviations. However, the value of these data depends on the ability to process signals rapidly and translate them into maintenance action.

In the United States, predictive maintenance is applied across diverse industrial assets, including turbines, robotics systems, aerospace production equipment, automotive assembly lines, additive manufacturing systems, and energy infrastructure. Edge AI improves maintenance responsiveness by detecting anomalies locally, reducing dependence on constant cloud connectivity, and enabling real-time alerts. In geographically distributed manufacturing environments, edge-based maintenance analytics can also reduce data-transfer costs and improve operational continuity.

In Taiwan, predictive maintenance is particularly critical in semiconductor fabrication and electronics manufacturing. Equipment failure in semiconductor production can cause costly downtime, yield loss, and quality deviations. Edge AI supports real-time monitoring of process equipment, vacuum systems, deposition tools, lithography support systems, inspection devices, and automated material-handling systems. Local anomaly detection allows engineers to respond before deviations propagate through production batches. This is especially important because semiconductor manufacturing involves complex process sequences where small disturbances can generate substantial downstream losses.

The comparison demonstrates that predictive maintenance is not a single technological application but a system capability linking sensors, models, decision rules, maintenance teams, and production priorities. The United States benefits from flexible application across asset types, while Taiwan benefits from dense process integration in high-value manufacturing environments. Both cases confirm that predictive maintenance contributes to reliability engineering by reducing unplanned downtime, improving asset availability, and extending equipment life.

This finding aligns with Carvalho et al. (2019) and Zonta et al. (2020), who identify machine learning as a critical enabler of predictive maintenance. However, this article extends those studies by emphasizing the role of computational location. Predictive maintenance based on edge AI can reduce decision latency and improve resilience when cloud connectivity is limited or when immediate operational intervention is required. From a sustainability perspective, predictive maintenance also reduces waste by preventing defective production, unnecessary replacement, and inefficient equipment operation.

3. Autonomous Control, Quality Optimization, and Process Adaptation

The third finding concerns the relationship between autonomous control and manufacturing quality. Edge AI enables manufacturing systems not only to detect anomalies but also to adjust operational parameters locally. Autonomous control can regulate machine speed, temperature, robotic movement, pressure, tool compensation, inspection thresholds, and energy use. The degree of autonomy differs across the United States and Taiwan due to differences in sectoral diversity and production specialization.

In the United States, autonomous control is prominent in advanced robotics, aerospace systems, additive manufacturing, semiconductor facilities, and high-value industrial automation. However, adoption varies significantly across sectors. Some industries use autonomous control for high-precision tasks such as robotic welding, additive manufacturing layer optimization, or machine-vision quality inspection. Other industries remain cautious due to safety certification, legacy equipment, labor relations, and regulatory complexity. This reflects operational constraints within a diversified industrial economy where autonomy must be adapted to heterogeneous production environments.

Taiwan’s autonomous control systems are more deeply integrated into precision manufacturing workflows. Semiconductor and electronics production require continuous process stabilization, where deviations in temperature, humidity, chemical composition, vibration, or timing can affect yield. Autonomous control allows systems to adjust parameters based on real-time sensor data and predictive models. This enables tighter control loops and reduces dependence on delayed human intervention. Taiwan's advantage lies in high process discipline, dense sensor integration, and strong alignment between automation and production objectives.

The comparison reveals technological divergence in the function of autonomy. In the United States, autonomy often supports flexibility, experimentation, and advanced manufacturing innovation. In Taiwan, autonomy supports stability, yield, and process precision. These differences suggest that autonomous control should be evaluated according to the operational problem being addressed. Flexibility-oriented autonomy differs from precision-oriented autonomy in design requirements, validation procedures, and risk tolerance.

This finding contributes to engineering optimization theory by showing that autonomous control functions as a bridge between prediction and performance. AI prediction alone does not improve manufacturing outcomes unless the system can act upon predictive insight. Autonomous control operationalizes AI by converting analytics into machine-level adjustment. However, autonomy also creates governance challenges, including model validation, safety assurance, accountability, and human oversight. Therefore, autonomous manufacturing requires carefully designed human-machine interaction rather than uncontrolled algorithmic decision-making.

4. Energy Efficiency, Computational Demand, and Sustainability Trade-Offs

The fourth finding is that edge AI and Industrial IoT can improve manufacturing energy efficiency, but they also introduce computational energy demands that must be governed. Manufacturing systems consume energy through machines, motors, robotics, heating, cooling, compressed air, cleanroom systems, data infrastructure, and material processing. AI-enabled monitoring can identify abnormal consumption, optimize production schedules, reduce idle energy use, and coordinate equipment operation with energy constraints. Yet intelligent manufacturing also requires sensors, edge processors, network infrastructure, data storage, and AI model maintenance.

In the United States, energy-efficiency applications of edge AI are distributed across sectors. Industrial facilities can use edge analytics to optimize motor systems, compressed air networks, thermal processes, building energy systems, and production scheduling. Energy-intensive manufacturing can benefit from real-time monitoring that detects inefficient operation and supports adaptive control. However, the diversified nature of US manufacturing means that sustainability benefits vary widely depending on firm capability, energy prices, regulatory context, and digital maturity.

In Taiwan, energy efficiency is particularly important because semiconductor manufacturing is electricity-intensive and requires controlled environments, cleanrooms, cooling, ultrapure water systems, and continuous process stability. Edge AI can improve equipment efficiency, reduce process deviations, optimize cooling systems, and prevent energy waste associated with defective production. However, Taiwan's semiconductor-centered industrial system also faces significant energy-security and sustainability pressures because high-performance manufacturing depends on reliable electricity and water supply.

The comparison demonstrates that sustainability outcomes depend on net-system performance. Edge AI can reduce energy waste at machine and process levels, but industrial digitalization can increase electricity demand through computation and data infrastructure. This reflects a broader engineering paradox: digital systems can improve sustainability while also consuming additional resources. Therefore, sustainability assessment must include both operational efficiency gains and the environmental footprint of digital infrastructure.

This finding aligns with Bonilla et al. (2018) and Javaid et al. (2022), who argue that Industry 4.0 technologies can support sustainability while creating new challenges. The article extends this literature by specifying the role of edge computing. Edge AI may reduce cloud data-transfer energy and latency, but widespread deployment of edge devices also increases hardware and maintenance requirements. Sustainable edge AI therefore requires energy-aware model design, efficient hardware, lifecycle assessment, and integration with industrial energy-management systems.

5. Cybersecurity, Data Governance, and Engineering Resilience

The fifth finding is that edge AI and Industrial IoT increase both resilience capability and cyber-physical vulnerability. Smart manufacturing systems rely on connected sensors, controllers, edge devices, cloud platforms, industrial networks, and autonomous control loops. These connections improve visibility and adaptability, but they also create attack surfaces. Cybersecurity is therefore not a secondary information-technology issue but a core engineering requirement.

In the United States, cybersecurity challenges are shaped by industrial diversity, legacy infrastructure, supply-chain complexity, and uneven digital maturity. Advanced firms may implement secure industrial networks, zero-trust architectures, and model-governance systems, while smaller firms may face resource constraints. The US industrial ecosystem benefits from strong cybersecurity research and technology providers, but implementation remains uneven across sectors.

In Taiwan, cybersecurity risk is closely linked to semiconductor supply-chain criticality and geopolitical exposure. Because Taiwan occupies a globally strategic position in semiconductor manufacturing, cyber-physical resilience is essential not only for firm-level continuity but also for global technology supply chains. Edge AI may strengthen resilience by enabling local decision-making when cloud systems are disrupted, but it also requires secure device management, model integrity protection, and trusted data pipelines.

The comparison reveals that engineering resilience depends on the capacity to maintain safe, reliable, and optimized function under disruption. Hollnagel's (2014) resilience engineering framework emphasizes monitoring, responding, learning, and anticipating. Edge AI strengthens monitoring and response by enabling local analytics and control. Industrial IoT strengthens anticipation by expanding visibility across equipment and processes. However, resilience is weakened if systems are vulnerable to cyber manipulation, model drift, or data corruption.

This finding contributes to engineering governance scholarship by demonstrating that intelligent manufacturing resilience requires secure autonomy. Autonomous systems must be explainable, validated, monitored, and overrideable. Cybersecurity, model governance, and human accountability must be embedded into system design. A manufacturing system that is optimized but insecure cannot be considered resilient or sustainable.

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

Variable	United States	Taiwan	Empirical/Simulation Evidence	Analytical Interpretation
Industrial structure	Large, diversified, AI-intensive manufacturing ecosystem across aerospace, automotive, energy, medical devices, and semiconductors	Specialized, semiconductor-centered, precision electronics manufacturing ecosystem	OECD, WEF, and sectoral engineering literature identify both as advanced industrial technology ecosystems	Industrial structure shapes the operational role of edge AI
Edge AI architecture	Distributed and heterogeneous across sectors and firm sizes	Dense, process-integrated, and precision-oriented in semiconductor and electronics production	Edge computing literature shows latency reduction and local inference benefits	The US gains flexibility; Taiwan gains process precision
Industrial IoT integration	Uneven but expanding across advanced manufacturing sectors	Highly integrated in high-value precision manufacturing environments	Industrial IoT studies link sensor networks to predictive maintenance and process monitoring	Data density increases predictive capability when interoperability is strong
Predictive maintenance	Broad application across varied industrial assets	Critical for semiconductor equipment reliability and yield protection	Predictive maintenance literature shows AI improves fault detection and downtime reduction	Maintenance value depends on asset criticality and response capability
Autonomous control	Strong in	Deeply integrated	Autonomous control improves	Autonomy supports

	advanced sectors but uneven due to regulatory, legacy, and safety constraints	into process stabilization and quality control	adaptive response when validated and supervised	flexibility in the US and stability in Taiwan
Energy optimization	Sector-specific energy savings through machine-level monitoring and adaptive scheduling	High strategic importance due to electricity-intensive semiconductor production	IEA evidence emphasizes industry as a major energy-demand sector	Sustainability depends on net efficiency gains versus digital energy demand
Cybersecurity resilience	Strong research capability but uneven implementation across firms	High strategic urgency due to semiconductor supply-chain criticality	Cyber-physical systems literature identifies expanded attack surfaces in connected manufacturing	Resilience requires secure edge devices, trusted data, and model governance
Workforce capability	Strong AI and software expertise but manufacturing skills vary regionally	Strong process engineering and precision manufacturing expertise	OECD evidence highlights uneven AI adoption and skills divides	Human capability mediates technological effectiveness
Sustainability implication	Potential for broad industrial energy optimization across sectors	Potential for high-impact efficiency in semiconductor-intensive production	Sustainability literature links Industry 4.0 with resource efficiency and new digital burdens	Sustainable outcomes require energy-aware AI and governance alignment

The analytical matrix demonstrates that edge AI and Industrial IoT performance cannot be evaluated independently from industrial structure. The United States benefits from breadth, innovation diversity, and strong AI research capacity, but its implementation challenge lies in uneven adoption and legacy system integration. Taiwan benefits from specialization, dense process integration, and high-value precision manufacturing, but its challenge lies in energy dependence, supply-chain concentration, and cyber-physical exposure.

The deeper interpretation is that intelligent manufacturing performance emerges from causal alignment among sensing, computation, control, governance, and sustainability. Sensors generate data, but data require interoperability. Edge AI generates prediction, but prediction requires validated models. Autonomous control generates adaptation, but adaptation requires safety assurance. Optimization improves productivity, but productivity must be aligned with energy efficiency and resilience. Therefore, the central engineering challenge is not simply to adopt AI, but to build socio-technical systems capable of converting distributed intelligence into reliable, secure, and sustainable operational performance.

Conceptual Model: Edge AI-Enabled Predictive Manufacturing for Sustainable Industrial Development

This article proposes the following conceptual engineering model:

Sensorized Industrial Infrastructure → Edge AI Predictive Analytics → Autonomous Control → Operational Optimization → Engineering Resilience → Sustainable Socio-Technical Development

Sensorized industrial infrastructure forms the foundation of intelligent manufacturing. It includes Industrial IoT sensors, machine controllers, robotics systems, energy meters, inspection devices, and production databases. These systems generate real-time operational data required for predictive analytics.

Edge AI predictive analytics transforms local industrial data into actionable intelligence. By processing data near machines and production assets, edge AI reduces latency, lowers bandwidth dependency, improves local decision-making, and strengthens operational continuity.

Autonomous control converts predictive insight into operational action. This includes machine parameter adjustment, robotic correction, process stabilization, energy-aware scheduling, and quality-control adaptation. Autonomous control is the mechanism through which AI moves from prediction to engineering performance.

Operational optimization emerges through reduced downtime, improved quality, lower defect rates, increased equipment availability, improved energy efficiency, and adaptive production scheduling. These outcomes are measurable expressions of intelligent manufacturing performance.

Engineering resilience develops when manufacturing systems can anticipate disruption, respond locally, maintain function, and recover rapidly. Edge AI strengthens resilience by enabling decentralized response, while Industrial IoT enhances monitoring and learning.

Sustainable socio-technical development occurs when operational gains are aligned with energy efficiency, cybersecurity, workforce adaptation, ethical AI governance, and long-term industrial competitiveness. The model demonstrates that sustainable manufacturing requires integration between technical systems and institutional capacities.

Conclusion

This study examined how edge AI, Industrial IoT, and autonomous control systems influence predictive manufacturing performance, operational optimization, engineering resilience, and sustainability outcomes in the United States and Taiwan. The findings demonstrate that edge AI improves manufacturing performance by reducing decision latency, enabling local anomaly detection, supporting predictive maintenance, strengthening autonomous control, and improving energy-aware optimization. However, these outcomes depend on industrial structure, data interoperability, cybersecurity governance, workforce capability, and sustainability alignment.

The direct answer to the research objective is that edge AI and Industrial IoT enhance predictive manufacturing when they convert sensorized operational data into low-latency intelligence and autonomous action. In the United States, these technologies support flexible innovation across diversified manufacturing sectors, although implementation remains uneven across firms and industries. In Taiwan, they support high-precision process control and semiconductor manufacturing reliability, although sustainability and resilience challenges are intensified by energy dependence and supply-chain concentration.

The theoretical contribution of this article lies in integrating edge computing architecture, cyber-physical systems theory, predictive maintenance, autonomous control, resilience engineering, and sustainability engineering within one comparative framework. The article advances engineering and applied science scholarship by demonstrating that computational location is a critical variable in smart manufacturing performance. Edge AI is not merely a technical extension of cloud computing; it reorganizes the relationship between sensing, prediction, control, and resilience.

The empirical and technological contribution lies in comparing two advanced industrial ecosystems using institutional data, automation indicators, and engineering literature. The findings show that the United States and Taiwan represent different pathways toward intelligent manufacturing. The United States demonstrates broad AI-enabled industrial experimentation, while Taiwan demonstrates dense precision integration. Both pathways produce valuable engineering outcomes, but both require governance mechanisms to manage cybersecurity, workforce adaptation, computational energy demand, and technological dependency.

The industrial implications are substantial. Manufacturers should design edge AI systems according to operational risk, latency requirements, equipment criticality, and energy performance. Predictive maintenance should be integrated with quality control, autonomous control, and energy management. Autonomous systems should remain transparent, validated, secure, and compatible with human oversight. Industrial IoT deployment should prioritize interoperability and cybersecurity rather than sensor expansion alone.

The policy implications are equally important. Governments should support industrial AI adoption through secure digital infrastructure, interoperability standards, workforce training, semiconductor supply-chain resilience, and sustainable manufacturing incentives. Policies should recognize that AI-enabled manufacturing can improve productivity and sustainability but may also increase cyber risk, energy demand, and inequality between digitally advanced and lagging firms.

The study has limitations. It relies on secondary evidence and comparative systems interpretation rather than plant-level experimental datasets. Cross-national differences in reporting standards and firm confidentiality limit direct quantitative comparison. Future research should develop edge AI maturity indices, conduct plant-level performance studies, measure latency-energy trade-offs, evaluate lifecycle impacts of edge hardware, and compare additional semiconductor and diversified manufacturing ecosystems.

Overall, this article concludes that edge AI, Industrial IoT, and autonomous control are becoming foundational infrastructures of sustainable predictive manufacturing. Their long-term contribution depends not only on algorithmic performance but on the alignment of engineering systems, human expertise, secure governance, energy efficiency, and socio-technical resilience.

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