
| RESEARCH ARTICLE

AI and Analytics for Smart Factories: Engineering Applications

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| ABSTRACT

The convergence of artificial intelligence, cloud analytics, and Internet of Things technologies has fundamentally transformed traditional manufacturing environments into intelligent, self-optimizing ecosystems known as smart factories. This article examines the practical implementation of AI-driven technologies in manufacturing contexts, focusing on digital twin applications, real-time process monitoring systems, and machine learning algorithms that enable predictive maintenance and production optimization. The article employs mixed-methods analysis combining case studies, performance metrics evaluation, and engineering workflow assessment to understand how these technologies reshape manufacturing operations and engineering practices. Key findings reveal significant improvements in operational efficiency, quality control, and resource utilization through the integration of predictive analytics and automated optimization systems. The article documents a fundamental shift in engineering roles from reactive maintenance approaches to proactive, data-driven decision-making processes that leverage human expertise alongside algorithmic intelligence. Technical challenges, including system integration complexities, data synchronization requirements, and cybersecurity considerations, present ongoing implementation hurdles that manufacturing organizations must address. The article identifies critical success factors for smart factory deployment, including workforce training programs, organizational change management strategies, and collaborative frameworks that facilitate effective human-machine interaction. Results demonstrate that smart factories enable manufacturing organizations to achieve enhanced competitiveness through reduced downtime, improved product quality, and optimized resource allocation while creating new requirements for engineering education and professional development. The article contributes to understanding how AI and analytics function as practical engineering enablers rather than abstract technological concepts, establishing smart factories as collaborative environments where data, machinery, and human expertise integrate to deliver continuous innovation and operational excellence in modern manufacturing contexts.

| KEYWORDS

Smart Factories, Digital Twin Technology, AI-Driven Manufacturing, Predictive Maintenance, Industrial IoT Analytics

| ARTICLE INFORMATION

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1. Introduction

The manufacturing landscape has undergone a profound transformation over the past decade, evolving from traditional production models to sophisticated, interconnected ecosystems known as smart factories. This evolution represents more than technological advancement; it embodies a fundamental shift in how engineers approach manufacturing challenges, moving from reactive maintenance strategies to predictive, data-driven optimization frameworks. Modern smart factories integrate artificial intelligence, cloud analytics, and Internet of Things technologies to create self-monitoring and self-optimizing production environments that respond dynamically to operational demands.

Contemporary manufacturing facilities now operate as complex networks where physical machinery communicates continuously with digital systems, generating vast streams of operational data that inform real-time decision-making processes. Engineers working within these environments find their traditional roles expanding beyond equipment maintenance and process

supervision to encompass data interpretation, algorithm optimization, and human-machine collaboration. The integration of digital twin technology allows manufacturing teams to create virtual representations of production lines, enabling risk-free testing of process modifications and predictive analysis of system performance under various operational scenarios.

The convergence of artificial intelligence with established engineering principles has created unprecedented opportunities for manufacturing optimization. Machine learning algorithms now analyze production patterns, identify inefficiencies, and recommend adjustments faster than human operators can process the same information. Cloud-based analytics platforms collect data from thousands of sensors embedded throughout production facilities, providing engineers with comprehensive visibility into machine health, resource utilization, and production flow dynamics. This technological synthesis enables manufacturing operations to achieve near-zero downtime while maintaining consistent product quality and optimizing resource consumption.

Smart factory implementations demonstrate how theoretical advances in artificial intelligence translate into practical engineering solutions that address real-world manufacturing challenges. The shift from scheduled maintenance protocols to condition-based monitoring represents a paradigm change that reduces operational costs while improving system reliability [1]. These developments signal a broader transformation where engineering expertise combines with algorithmic intelligence to create manufacturing environments capable of continuous self-improvement and adaptation to changing market demands.

2. Literature Review

2.1 Smart Factory Fundamentals

The evolution of automated manufacturing systems traces back to early programmable logic controllers in the 1970s, progressing through computer-integrated manufacturing in the 1980s to today's cyber-physical production systems. Smart factory ecosystems comprise interconnected components, including industrial IoT sensors, edge computing devices, cloud infrastructure, and human-machine interfaces that collectively enable autonomous decision-making capabilities [2]. Integration challenges persist in legacy system compatibility, standardization across vendor platforms, and ensuring cybersecurity in networked manufacturing environments. Technological prerequisites include robust network infrastructure, standardized communication protocols, and scalable data processing capabilities that support real-time operational requirements.

2.2 AI and Machine Learning in Manufacturing

Reinforcement learning algorithms demonstrate significant potential in production optimization by learning optimal control policies through interaction with manufacturing environments, particularly in scheduling and resource allocation tasks. Predictive analytics applications extend beyond traditional maintenance scheduling to encompass quality control systems that identify defective products before they reach end-of-line inspection points. Cloud-based analytics platforms provide manufacturers with scalable computational resources for processing large datasets, enabling complex pattern recognition and anomaly detection across multiple production facilities simultaneously.

2.3 Digital Twin Technology

Digital twin technology builds upon simulation modeling principles, incorporating real-time data synchronization to create dynamic virtual representations of physical manufacturing assets. Manufacturing applications range from process optimization and what-if scenario testing to predictive maintenance scheduling based on virtual system behavior analysis [3]. Real-time synchronization presents ongoing challenges in data latency, model accuracy maintenance, and computational resource management, particularly when scaling digital twin implementations across complex multi-line production facilities.

2.4 IoT and Sensor Integration

Industrial sensor networks encompass temperature, vibration, pressure, and vision systems distributed throughout manufacturing environments to monitor equipment performance and product quality parameters. Data collection protocols must balance transmission frequency with network bandwidth limitations while ensuring critical information reaches decision-making systems without delay. Real-time monitoring architectures typically employ edge computing nodes to process sensor data locally, reducing network traffic while enabling immediate response to critical operational events.

3. Methodology

3.1 Research Design

This investigation employs a mixed-methods approach combining quantitative analysis of manufacturing performance data with qualitative assessment of engineering workflow transformations. Case study methodology focuses on smart factory implementations across different industry sectors, while structured surveys capture engineering professional perspectives on technology adoption impacts. Industry survey methodology incorporates both online questionnaires and in-person interviews to assess how AI integration affects daily engineering practices and decision-making processes.

3.2 Data Collection

Primary data collection involves direct measurement of operational metrics from participating smart factory facilities, including production throughput, equipment downtime, and quality indicators. Secondary data sources encompass published manufacturing performance benchmarks, industry reports on automation adoption rates, and academic studies on AI implementation outcomes [4]. Expert interviews with engineering professionals provide qualitative insights into workflow changes, skill development needs, and practical challenges encountered during smart factory transitions.

3.3 Analysis Framework

Performance evaluation metrics include overall equipment effectiveness, mean time between failures, and production scheduling efficiency to quantify AI-driven optimization impacts. Comparative analysis examines operational differences between traditional manufacturing approaches and smart factory methodologies using standardized performance indicators. Engineering workflow transformation assessment utilizes task analysis techniques to document changes in job responsibilities, decision-making authority, and collaboration patterns within AI-integrated manufacturing environments.

Technology Component	Primary Applications	Key Benefits	Implementation Challenges
Digital Twins	Process simulation, virtual testing	Risk-free optimization, predictive analysis	Real-time synchronization, model accuracy
IoT Sensors	Equipment monitoring, data collection	Continuous visibility, early fault detection	Data quality, network reliability
AI Algorithms	Workload balancing, demand response	Automated optimization, bottleneck resolution	System integration, algorithm validation
Cloud Analytics	Data processing, pattern recognition	Scalable computing, multi-facility analysis	Cybersecurity, data transmission latency

Table 1: Smart Factory Technology Components and Applications [2 -5]

4. Core Technologies and Applications

4.1 Digital Twin Implementation

Digital twin technical architecture requires high-performance computing infrastructure capable of processing continuous data streams from physical assets while maintaining synchronized virtual models. System requirements include edge computing nodes for local data processing, secure communication channels for real-time data transmission, and scalable cloud storage for historical data analysis. Real-time simulation capabilities depend on accurate mathematical models that reflect physical system behavior, with simulation accuracy directly correlating to sensor data quality and model calibration frequency [5]. Process optimization through virtual testing enables manufacturers to evaluate production changes without disrupting actual operations, reducing implementation risks, and optimizing resource allocation decisions.

Successful digital twin deployments demonstrate measurable improvements in operational efficiency across various manufacturing sectors. Aerospace manufacturers utilize digital twins for predictive maintenance scheduling, while automotive producers employ virtual models for production line optimization and quality control enhancement.

4.2 Real-Time Process Monitoring Systems

IoT sensor integration requires robust data pipeline architectures that handle diverse sensor types, communication protocols, and data formats while ensuring reliable transmission to central processing systems. Cloud analytics platforms provide manufacturers with scalable computational resources for real-time data processing, pattern recognition, and anomaly detection across multiple production facilities simultaneously. Machine health monitoring systems utilize vibration analysis, thermal imaging, and acoustic sensors to identify equipment degradation patterns before failures occur, enabling proactive maintenance interventions.

Production flow visualization interfaces present complex manufacturing data through intuitive dashboards that allow operators to monitor system performance, identify bottlenecks, and coordinate response actions. Control interfaces integrate with existing manufacturing execution systems to provide seamless workflow management and automated response capabilities.

4.3 AI-Driven Optimization Algorithms

Reinforcement learning applications in workload balancing demonstrate significant potential for optimizing production scheduling across multiple manufacturing lines, learning optimal resource allocation strategies through continuous interaction with production environments. Supply chain synchronization employs advanced analytics to coordinate material flows, inventory levels, and production schedules across interconnected facilities and supplier networks [6]. Dynamic demand response systems adjust production parameters in real-time based on market fluctuations, customer orders, and resource availability constraints.

Bottleneck identification strategies utilize machine learning algorithms to analyze production flow data, identifying constraint points that limit overall system throughput. Resolution strategies encompass automated resource reallocation, priority adjustment, and alternative routing options that maintain production targets while minimizing operational disruptions.

5. Engineering Impact and Role Transformation

5.1 From Reactive to Proactive Engineering

Traditional monitoring approaches rely on scheduled inspections and reactive maintenance responses to equipment failures, while predictive intervention systems analyze continuous data streams to identify potential issues before they impact production operations. Enhanced decision-making capabilities emerge from data-driven insights that provide engineers with comprehensive system visibility, enabling informed choices about maintenance timing, resource allocation, and process optimization strategies. Integration of human expertise with AI recommendations creates collaborative decision-making environments where engineering knowledge combines with algorithmic analysis to achieve optimal operational outcomes [7].

5.2 Skill Set Evolution

AI-integrated manufacturing environments require engineers to develop competencies in data analysis, machine learning interpretation, and human-machine interface management alongside traditional technical skills. Training programs must address knowledge gaps in statistical analysis, algorithm understanding, and digital system integration while maintaining focus on fundamental engineering principles. Collaborative workflows between engineers and AI systems necessitate new communication protocols, decision-making frameworks, and quality assurance procedures that ensure effective human-machine cooperation.

Adaptation challenges include resistance to technology change, learning curve management, and maintaining engineering judgment while leveraging algorithmic recommendations. Professional development initiatives focus on bridging traditional engineering education with modern data science applications.

5.3 Operational Efficiency Gains

Manufacturing facilities implementing AI-driven optimization report significant downtime reduction through predictive maintenance strategies and automated fault detection systems. Resource utilization improvements result from intelligent scheduling algorithms that optimize equipment usage, energy consumption, and material flows across production operations. Quality improvement metrics demonstrate enhanced product consistency, reduced defect rates, and improved customer satisfaction through real-time quality monitoring and automated correction systems.

Quantitative analysis reveals measurable improvements in overall equipment effectiveness, production throughput, and cost per unit manufactured. These efficiency gains translate directly into competitive advantages and improved profitability for manufacturing organizations adopting smart factory technologies.

Traditional Engineering Approach	Smart Factory Engineering Approach	Technology Enabler	Skill Requirements
Scheduled maintenance inspections	Predictive maintenance interventions	AI analytics, sensor data	Data interpretation, algorithm understanding
Reactive problem solving	Proactive optimization system	Digital twins, simulation	Virtual testing, model validation
Manual process monitoring	Automated real-time monitoring	IoT networks, dashboards	Human-machine interface management
Individual decision-making	Collaborative human-AI workflows	Machine learning recommendations	AI system integration, collaborative protocols

Table 2: Engineering Role Transformation in Smart Factory Environments [7]

6. Results and Analysis

6.1 Performance Metrics

Smart factory implementations demonstrate measurable efficiency improvements across multiple operational dimensions, with manufacturing facilities reporting enhanced throughput rates and reduced cycle times through optimized production scheduling algorithms. Downtime reduction emerges as a primary benefit of predictive maintenance systems, which identify equipment degradation patterns before critical failures occur, enabling planned maintenance interventions that minimize production interruptions. Quality control enhancement through AI analytics enables real-time defect detection and process adjustment, resulting in improved product consistency and reduced waste generation throughout manufacturing operations.

Performance data indicates substantial improvements in overall equipment effectiveness metrics, with many facilities achieving higher utilization rates and improved production yield through intelligent resource allocation and automated process optimization systems.

6.2 Cost-Benefit Analysis

Implementation costs for smart factory technologies encompass hardware procurement, software licensing, system integration services, and workforce training programs, representing significant upfront investments that require careful financial planning and justification. Operational savings materialize through reduced maintenance costs, lower energy consumption, decreased waste generation, and improved labor productivity, creating positive cash flows that offset initial technology investments over time. ROI timelines for smart factory investments typically range from two to five years, depending on implementation scope, existing infrastructure conditions, and operational complexity factors [8].

Long-term sustainability considerations include ongoing technology maintenance costs, system upgrade requirements, and continuous workforce development needs that must be factored into total cost of ownership calculations for manufacturing organizations.

6.3 Engineering Workflow Transformation

Daily engineering practices have evolved from scheduled inspection routines and reactive problem-solving approaches to data-driven analysis and proactive system optimization activities. Enhanced problem-solving capabilities result from comprehensive system visibility provided by integrated monitoring platforms, enabling engineers to identify root causes more efficiently and implement targeted solutions that address underlying operational issues. Improved collaboration between human expertise and AI systems creates synergistic relationships where engineering knowledge guides algorithmic optimization while data analytics inform engineering decision-making processes.

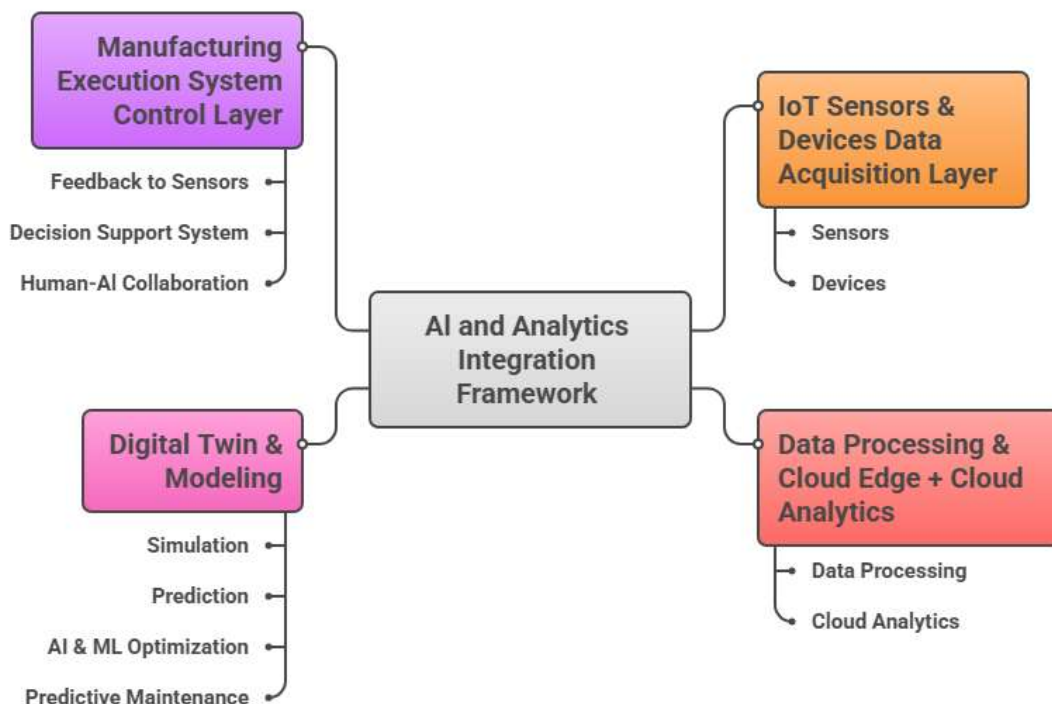


Figure 01. AI and Analytics Integration Framework for Smart Factory Engineering

Workflow transformation includes modified communication protocols, updated documentation procedures, and restructured responsibility assignments that accommodate human-machine collaboration requirements in modern manufacturing environments.

Performance Indicator	Traditional Manufacturing	Smart Factory Implementation	Improvement Method
Equipment Downtime	Scheduled + Unplanned failures	Predictive maintenance windows	AI-driven fault prediction
Quality Control	End-of-line inspection	Real-time defect detection	Continuous monitoring systems
Resource Utilization	Static scheduling	Dynamic allocation	Optimization algorithms
Decision Response Time	Hours to days	Real-time to minutes	Automated analytics processing
Production Flexibility	Limited adaptation	Dynamic demand response	AI-driven scheduling

Table 3: Performance Metrics Comparison: Traditional vs. Smart Factory Operations [8]

7. Challenges and Limitations

7.1 Technical Challenges

System integration complexities arise from incompatible communication protocols, legacy equipment limitations, and diverse vendor platforms that require extensive customization and interface development to achieve seamless operation. Data quality and synchronization issues present ongoing challenges in maintaining accurate real-time information across distributed manufacturing systems, particularly when combining historical data with live sensor feeds from multiple sources. Cybersecurity concerns in connected manufacturing environments require comprehensive security frameworks that protect sensitive operational data while maintaining system accessibility for authorized users and processes [9].

Network reliability, data storage capacity, and computational resource management represent additional technical hurdles that must be addressed during smart factory implementation and ongoing operation phases.

7.2 Organizational Challenges

Change management initiatives must address workforce concerns about technology adoption, job security, and skill development requirements while maintaining operational continuity during transition periods. Investment requirements for smart factory technologies often exceed traditional capital expenditure budgets, necessitating strategic financial planning and stakeholder alignment to secure necessary funding and resources. Regulatory compliance and industry standards present evolving requirements that manufacturing organizations must navigate while implementing new technologies and operational procedures.

Workforce adaptation challenges include training program development, performance evaluation criteria updates, and organizational structure modifications that accommodate new roles and responsibilities in AI-integrated manufacturing environments.

7.3 Future Research Needs

Emerging technologies, including quantum computing, advanced robotics, and next-generation artificial intelligence algorithms, present potential applications that require systematic investigation and validation within manufacturing contexts. Standardization requirements for interoperability remain critical research areas, particularly regarding communication protocols, data formats, and security frameworks that enable seamless integration across diverse manufacturing systems and vendor platforms.

Sustainability and environmental impact considerations demand a comprehensive analysis of energy consumption patterns, waste generation reduction potential, and lifecycle assessment methodologies for smart factory technologies. Research priorities include developing optimization algorithms that balance operational efficiency with environmental responsibility while maintaining economic viability for manufacturing organizations.

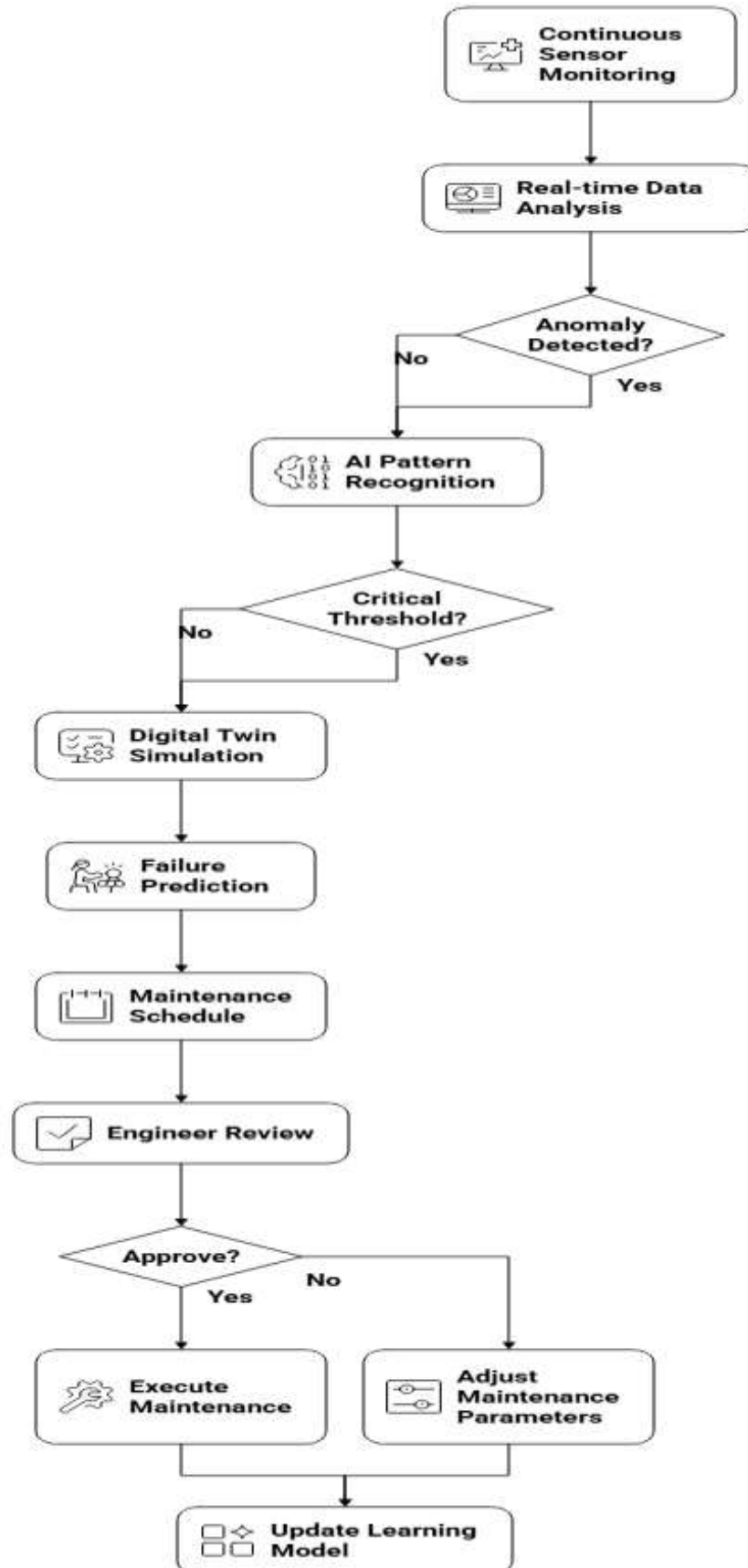


Figure 2: AI - Driven Maintenance Process

8. Future Directions and Implications

8.1 Technological Advancements

Next-generation AI algorithms for manufacturing focus on explainable artificial intelligence systems that provide transparent decision-making processes, enabling engineers to understand and validate algorithmic recommendations before implementation. Enhanced digital twin capabilities will incorporate advanced physics-based modeling, real-time machine learning updates, and multi-scale simulation environments that bridge molecular-level material properties with system-wide production optimization. Advanced sensor technologies, including wireless mesh networks, self-powered IoT devices, and quantum sensors, promise improved data collection accuracy, while edge computing developments enable sophisticated local processing capabilities that reduce network latency and enhance real-time response performance.

Technological convergence between artificial intelligence, robotics, and materials science creates opportunities for autonomous manufacturing systems that adapt continuously to changing operational conditions and product requirements.

8.2 Industry Transformation Trends

Adoption patterns across manufacturing sectors reveal varying implementation speeds, with automotive and electronics industries leading smart factory deployment while traditional sectors like textiles and food processing demonstrate more gradual technology integration approaches. Global competitiveness implications suggest that manufacturing regions investing heavily in smart factory technologies will gain significant advantages in production efficiency, quality consistency, and operational flexibility compared to areas relying on conventional manufacturing methods [10]. Supply chain resilience improvements through AI-driven optimization enable manufacturers to respond more effectively to disruptions, market fluctuations, and demand variations while maintaining production continuity and cost competitiveness.

Manufacturing ecosystems increasingly emphasize collaborative networks where multiple facilities share data, resources, and optimization strategies to achieve collective operational improvements and risk mitigation benefits.

8.3 Engineering Education and Training

Curriculum development for AI-integrated manufacturing requires fundamental changes in engineering education programs, incorporating data science principles, machine learning applications, and human-machine interface design alongside traditional mechanical, electrical, and industrial engineering coursework. Professional development programs must address knowledge gaps in existing workforce populations through targeted training initiatives that combine theoretical understanding with hands-on experience using smart factory technologies and analytical tools.

Industry-academia collaboration models facilitate knowledge transfer between research institutions developing cutting-edge technologies and manufacturing organizations implementing practical solutions. These partnerships create opportunities for student internships, faculty consulting arrangements, and joint research projects that accelerate technology adoption while preparing future engineers for careers in AI-integrated manufacturing environments.

Educational initiatives emphasize interdisciplinary learning approaches that combine engineering fundamentals with computer science applications, business management principles, and sustainability considerations essential for successful smart factory implementation and operation.

Challenge Category	Specific Issues	Potential Solutions	Research Priority
Technical	System integration complexity	Standardized protocols, modular architecture	Interoperability frameworks
Technical	Data quality synchronization	Edge computing, validation algorithms	Real-time data processing
Organizational	Workforce adaptation	Training programs, change management	Human-AI collaboration models
Economic	High implementation costs	Phased deployment, ROI optimization	Cost-benefit analysis methods
Security	Cybersecurity vulnerabilities	Multi-layer security frameworks	Manufacturing cybersecurity protocols

Table 4: Smart Factory Implementation Challenges and Solutions [9, 10]

9. Conclusion

The integration of artificial intelligence and analytics in smart factory environments represents a fundamental paradigm shift that transforms manufacturing from reactive, schedule-driven operations to proactive, data-driven ecosystems capable of continuous self-optimization. This comprehensive article demonstrates how digital twin technology, real-time process monitoring, and AI-driven optimization algorithms collectively enable unprecedented levels of operational efficiency, quality control, and predictive maintenance capabilities that were previously unattainable through conventional manufacturing approaches. The transformation extends beyond technological implementation to encompass profound changes in engineering roles, skill requirements, and collaborative workflows that blend human expertise with algorithmic intelligence. While technical challenges related to system integration, data quality, and cybersecurity remain significant hurdles, the documented performance improvements in downtime reduction, resource utilization, and quality metrics provide compelling evidence for continued smart factory adoption across manufacturing sectors. The evolution of engineering practice from passive monitoring to active optimization, supported by comprehensive data analytics and predictive modeling capabilities, positions smart factories as an essential competitive advantage in global manufacturing markets. Future developments in next-generation AI algorithms, enhanced sensor technologies, and standardized interoperability frameworks will further accelerate this transformation, necessitating corresponding evolution in engineering education programs and professional development initiatives. Smart factories ultimately represent the convergence of physical manufacturing expertise with digital intelligence, creating collaborative environments where data, machines, and human knowledge work in harmony to achieve continuous innovation, operational excellence, and sustainable manufacturing practices that define the future of industrial production.

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