Future Technology
Open Access Journal
ISSN 2832-0379

November 2025| Volume 04 | Issue 04 | Pages 267-281

Journal homepage: https://fupubco.com/futech

https://doi.org/10.55670/fpll.futech.4.4.22

Future Publishing LLC

Article

Research on risk control and sustainability strategies of AI-driven big data analytics in LEAN manufacturing equipment R&D

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ARTICLE INFO

Article history:
Received 29 June 2025
Received in revised form
20 August 2025
Accepted 04 September 2025

Keywords:
AI-LEAN integration,
Risk management,
Sustainability metrics,
Industry 4.0, Operational excellence

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DOI: 10.55670/fpll.futech.4.4.22

ABSTRACT

The convergence of artificial intelligence (AI) and LEAN manufacturing principles presents unprecedented opportunities for operational excellence while introducing complex risk management and sustainability challenges. Addressing the critical research gap in quantitative AI-LEAN integration models. This research develops an integrated framework for implementing AI-driven big data analytics in LEAN manufacturing equipment R&D, addressing the critical gap between technological capabilities and sustainable manufacturing practices. We used three research methods: theoretical modelling, empirical validation with the SECOM semiconductor dataset, and 12-month field testing across three manufacturing facilities. This mixed-methods approach quantifies the synergistic effects of AI-LEAN integration. The framework incorporates hierarchical risk taxonomy, real-time anomaly detection algorithms achieving 93.5% accuracy, and multidimensional sustainability metrics. Results demonstrate substantial improvements: 36.1% increase in overall equipment effectiveness, 58.9% reduction in setup times, and 31.4% decrease in carbon footprint, energy intensity reduced by 30%, employee safety incidents decreased by 67%, and job satisfaction increased by 15%, achieving synergistic optimization of environmental benefits and social value. Risk prediction models achieved 91-96% accuracy across different categories, while maintaining sub-50ms inference times for real-time applications. The AI-enhanced system outperformed traditional LEAN implementations by 1.81x in continuous improvement rates and achieved payback in 13 months versus 23 months for conventional approaches. Financial analysis reveals 319.4% ROI over five years, validating the economic viability alongside environmental benefits. This research establishes a replicable paradigm for sustainable smart manufacturing, demonstrating that advanced analytics can simultaneously enhance operational efficiency, risk management, and environmental stewardship while preserving LEAN's human-centric values.

1. Introduction

The manufacturing industry is undergoing a transformation, where the fusion of Industry 4.0 technologies and traditional Lean manufacturing is fundamentally changing production concepts. The introduction of lean manufacturing equipment research and development (R&D) with artificial intelligence (AI) and big data Analytics marks a significant paradigm shift with potential unprecedented efficiency gains, and an associated set of remarkably complex risk management and sustainability challenges [1]. With more companies targeting AI-based solutions, recent research shows that 78% of companies have implemented AI in at least one business function, compared to 55% a year ago.1 The rise of AI has made it essential to consider holistic frameworks that strike a proper balance between innovation and minimizing risk, alongside ensuring sustainable practices [2]. The rise of LEAN manufacturing in the era of Industry 4.0 has led to an overhaul of traditional waste reduction and continuous improvement approaches. Although LEAN has dominated industrial improvement methodologies since the 1990s, the combined integration of AI and digital technologies is creating what researchers call Lean Industry 4.0 —a socio-technical model that involves humans and AI in a system, along with various digital technologies [3]. This integration has enabled manufacturers to achieve productivity increments of 6% or greater per year when appropriately implemented; however, the rapid pace of technology adoption often outpaces the development of necessary governance [4]. The difficulty then is not just to implement new technology and products productively in interaction with AI and LEAN methods, but to make AI and these LEAN methods work together profitably, while still working with the environment. Integrating AI and big data into the field of manufacturing equipment R&D is challenging, and the issues extend beyond technical concerns. An accompanying study reveals that 45% of manufacturers believe a lack of knowledge is the primary obstacle, and 44% encounter difficulties integrating AI solutions with their production facilities [5]. They become even more complex when addressing modern manufacturing, where AI-based demand forecasting systems interact with just-in-time production systems, reducing forecast errors by 20% to 50% while mitigating the risks associated with small buffers and short response lead times [6]. Additionally, when introducing AI into equipment development processes, it is essential to consider the quality of data input, the system's interoperability, and the preservation of tacit knowledge that is inherently encoded in conventional LEAN activities [7]. Despite growing interest in AI-LEAN integration, current research reveals significant limitations that hinder both theoretical advancements and practical implementations. The existing literature lacks comprehensive mathematical models that can quantify the synergistic effects between AI-LEAN and dynamic learning. Existing frameworks merely treat risk control, sustainability assessment, and operational optimization as discrete problems rather than integrated dimensions. Furthermore, there remains a dearth of long-term studies featuring rigorous controlled experimental comparisons across diverse manufacturing environments.

The increasing focus on risk management and sustainability in the context of smart manufacturing mirrors the more general changes in society and regulation. The EU's AI Act, which commenced in August 2024, represents the world's first-ever comprehensive legal framework for AI, where systems have been classified according to risk levels and specific requirements have been set for high-risk uses [8]. Likewise, sustainability reporting has evolved from a voluntary to a mandatory framework, with the Corporate Sustainability Reporting Directive mandating extensive environmental impact assessments [9]. Manufacturers are under more scrutiny than ever to prove that we are not just efficient, but we are also socially responsible, and we can be ethical in AI deployment [10].

New AI-based analytics in manufacturing is a fast-paced, high-investment area of research, but not without its challenges. Predictive maintenance, quality control, and supply chain optimization are becoming popular tasks of machine learning algorithms. On some systems, about 30% of equipment downtime is being reduced by AI-driven predictive analytics [11]. Deep learning methods in pattern recognition for defect detection and process optimization, and reinforcement learning are being further investigated for dynamic production scheduling in complex manufacturing scenarios [12]. However, the literature also emphasizes continued concerns with respect to model interpretability, patient privacy, and the possibility of algorithmic bias in the decision-making process [13]. LEAN principles in the equipment development process have long been centered on waste reduction, standard work, and continuous improvement. Recent works show that AI can support these principles with real-time optimization of the value stream and data-driven kaizen [14]. The connection of AI to LEAN has given rise to hybrid mechanisms that preserve the human-based approach of LEAN and combine it with the analytics of AI systems [15]. It is essential to emphasize that AI visual management systems and digital and on-board systems have shown a significant improvement in response time and problem-solving [16]. The risk assessment for smart manufacturing systems has been developed to address the specific issues associated with AI integration. The NIST AI Risk Management Framework, released in 2023 and subsequently expanded by specific profiles for generative AI, offers structured paths for identifying, assessing, and mitigating AI-related risks [17]. These models stress the importance of ongoing monitoring, stakeholder engagement, and having clear lines of accountability [18]. Centralized governance, risk, and compliance software is used in manufacturing institutions, as organizations have numerous departments in which the AI is deployed [19]. Sustainability measures and strategies in industrial R&D aren't just about the environment anymore – the scope has broadened to include social and economic aspects as well. New studies are suggesting combined sustainability indicators that include energy consumption, utilization of resources, carbon footprint, and social impact [20]. AI is being used to optimize these multiple objectives at once, but trade-offs exist between competing sustainability goals and production efficiency goals [21]. Notwithstanding these advances, the review of the literature identifies some research gaps where AI meets LEAN manufacturing and sustainable development. The studied fields are usually handled separately, which dismisses the intricate connections and possible synergies [22]. There is a paucity of empirical data regarding the long-term effects of AI implementation on the LEAN culture and culture-related workforce dynamics, as well as of integrated frameworks that facilitate the handling of technical, operational, and strategic risk factors in AI-based manufacturing contexts [23].

This study constructs an integrated framework that aims to integrate risk control and sustainability strategies into the research and development environment of AI-LEAN integration equipment. It establishes a hierarchical risk classification system, identifying key risk factors inherent in the technological, operational, strategic, and ethical dimensions of AI-lean manufacturing convergence. Concurrently, the research develops a multidimensional sustainability assessment indicator system to quantify the environmental, economic, and social impacts of AI integration initiatives on performance. The study also develops proactive risk mitigation strategies that leverage the technological advantages of AI systems while adhering to the core principle of continuous improvement within the lean manufacturing philosophy. The scope is confined to the R&D phase of manufacturing equipment, employing a mixed-methods approach that integrates theoretical modelling, empirical validation using the SECOM semiconductor dataset, and comprehensive 12-month field implementation verification across multiple manufacturing environments. This study makes an innovative contribution to the manufacturing science literature through its multidimensional approach, advancing both theoretical understanding and practical application of intelligent manufacturing systems. It proposes a comprehensive theoretical framework that explicitly integrates risk management and sustainability perspectives, addressing a key gap in existing literature where these domains are typically treated separately. The investigation quantifies AI-Lean synergies through mathematical modelling, establishing an operational performance assessment model for systematically evaluating and optimizing integrated systems. It provides empirically validated implementation guidelines that demonstrate how advanced analytical techniques can simultaneously enhance operational efficiency, risk control capabilities, and environmental management standards while upholding the core human-centered values of lean manufacturing. The framework's replicability and 319.4% return on investment within five years establish a new paradigm for sustainable smart manufacturing transformation, achieving a balance between technological advancement and organizational and environmental responsibility.

2. Literature review

2.1 AI-LEAN integration in industry 4.0

Recent investigations have demonstrated significant progress in integrating artificial intelligence with LEAN manufacturing principles within Industry 4.0 paradigms. Powell [1] explored the emerging roles of artificial intelligence in lean manufacturing, emphasizing the need for digitalization with a human touch. Tashkinov [21] proposed an interdisciplinary approach combining lean manufacturing principles with artificial intelligence to improve production system efficiency. Shahin [7] demonstrated that integrating Lean Manufacturing tools with artificial intelligence represents a revolutionary approach to optimizing production processes, reducing waste, and enhancing efficiency, where AI algorithms excel in pattern recognition, data analysis, and decision-making, offering more precise, data-driven solutions for manufacturing challenges. Saad [24] conducted a systematic review of the literature on Industry 4.0 and Lean Manufacturing integration, providing scholars with a better understanding of existing research and contributing to the definition of clear topics for future research opportunities. Saraswat [3] investigated the technological integration of lean manufacturing with Industry 4.0 toward lean automation through a systematic review.

2.2 Predictive maintenance and smart manufacturing applications

Predictive maintenance represents a critical convergence area where AI capabilities complement LEAN total productive maintenance principles. Ucar [25] reviewed recent developments in AI-based predictive maintenance, focusing on key components, trustworthiness, and future trends. Recent systematic multi-sector mapping reveals that within smart manufacturing contexts, predictive maintenance approaches can decrease downtimes, reduce operational costs, and increase productivity, improving system performance and decision-making across diverse manufacturing sectors. Achouch [26] provided a comprehensive overview of predictive maintenance in Industry 4.0, examining models and challenges while highlighting that data-driven predictive maintenance constitutes a cutting-edge solution with growing interest in modern manufacturing. Recent advances in smart manufacturing have demonstrated unified predictive maintenance platforms that leverage data warehousing, Apache Spark, and machine learning, addressing the heightened complexity in machinery and equipment used within collaborative manufacturing landscapes while presenting significant risks associated with equipment failures.

2.3 Sustainability integration and research gaps

Despite growing emphasis on sustainable manufacturing, systematic integration of sustainability metrics with AI-LEAN frameworks remains limited. Ghaithan [27] investigated the integrated impact of circular economy, Industry 4.0, and lean manufacturing on sustainability performance. Ciliberto [28] presented a sustainable lean manufacturing recipe for Industry 4.0 that enables a transition to a circular economy. Machado [29] identified interlinks between Industry 4.0 technologies and sustainable operations, discussing influences on sustainable business models and effects on lean manufacturing practices, while noting convergence about desirable features relating to being flexible, reconfigurable, low cost, adaptive, agile, and lean. Recent studies examining relationships between lean manufacturing, Industry 4.0, and sustainability reveal that while Industry 4.0 shows a strong correlation with sustainability pillars, the relationship between lean manufacturing and sustainability dimensions is not conclusive. Kipper [30] demonstrated that Industry 4.0 and lean manufacturing practices contribute to sustainable organizational performance in Indian manufacturing companies, achieving improvements in operational metrics while supporting environmental objectives. However, studies in the Mexican maquiladora industry reveal that while lean manufacturing tools are being applied in production lines, few investigations have examined the relationships with comprehensive sustainability dimensions that encompass social, economic, and environmental aspects. Research gaps identified include the absence of comprehensive risk taxonomies specific to AI-LEAN integration, limited quantification of sustainability synergies, and a lack of long-term empirical validation across multiple manufacturing contexts. Buer [31] demonstrated complementary effects of lean manufacturing and digitalization on operational performance.

3. Methodology

3.1 Theoretical framework development

We developed a theoretical framework for AI-LEAN integration. This framework combines proven LEAN principles with advanced AI methodologies. This integration necessitates careful consideration of how traditional continuous improvement paradigms can be enhanced through machine learning capabilities while preserving the human-centric values fundamental to LEAN philosophy. Our framework construction begins with the mathematical formalization of LEAN-AI synergies, proceeds through risk categorization specific to intelligent manufacturing systems, and culminates in a multidimensional sustainability assessment model. The integration of LEAN principles with AI-driven analytics represents a paradigm shift from reactive to predictive operational management. Traditional LEAN methodologies focus on waste elimination through visual management and standardized work. The traditional value stream efficiency (VSE) formula: ηVSM = Value-added time (VAT)/Total lead time (LT) [32]. While AI introduces capabilities for pattern recognition and optimization at scales beyond human cognitive capacity. We propose an enhanced value stream efficiency model that incorporates AI optimization factors:

$$VSE_{AI} = \frac{VAT}{LT} \times (1 + \gamma) \times \theta \times \phi \tag{1}$$

where VSE_{AI} denotes the AI-enhanced value stream efficiency, VAT represents value-added time in the production process, LT indicates total lead time including processing and waiting periods, γ is the AI-driven improvement factor ranging from 0 to 0.8, θ represents the data quality coefficient (0 to 1), and ϕ denotes the human-AI collaboration effectiveness factor (0.5 to 1.5).

The AI-driven improvement factor γ captures the incremental efficiency gains achieved through machine learning applications [33] and is calculated through the weighted sum across k=1 to 5 dimensions:

$$\gamma = \sum_{k=1}^{5} \alpha_k \times \beta_k \times (1 - e^{-\lambda_k t}) \tag{2}$$

where α_k represents the potential improvement in LEAN waste category k (overproduction, waiting, transport, overprocessing, inventory), β_k denotes the AI applicability factor for waste type k, λ_k is the learning rate coefficient, and t represents the time since AI implementation. $1 - e^{-\lambda_k t}$ is the index convergence term, modelling the temporal evolution of learning effects. The core distinction between AI-enhanced models and traditional LEAN efficiency assessments lies in dynamic modelling capabilities. This formulation introduces learning effect modelling through the exponential convergence term $1 - e^{-\lambda_k t}$, capturing the AI system's progressive improvement trajectory over time, whereas traditional LEAN methods rely on static efficiency level assumptions. Simultaneously, its five-dimensional summation structure provides a multifaceted comprehensive evaluation, offering greater breadth than conventional single-metric approaches. The parameterized learning rate λ_k for each dimension permits heterogeneous convergence speeds across different improvement aspects, grounded in empirical observational data rather than uniform theoretical assumptions. Mathematically, this method constitutes a multidimensional extension of empirical learning curve models, incorporating temporal dynamics beyond traditional static computations. However, it fundamentally represents a parametric refinement of existing LEAN efficiency assessment approaches rather than a foundational theoretical breakthrough.

Based on 12 months of manufacturing site validation, this modeling approach demonstrated significant improvements over traditional LEAN efficiency assessments across three manufacturing plants: predictive accuracy increased from 78% using conventional methods to 89%, while response times were reduced from several hours for manual evaluations to real-time computation. However, the method requires a minimum of six months' historical data for parameter λ_k calibration to operate effectively. The practical efficacy of this mathematical extension is highly contingent upon the digital maturity of the manufacturing environment and the caliber of available data.

In settings with inadequate digital infrastructure or limited data acquisition capabilities, its advantages over conventional methods may be markedly diminished or even negligible. Consequently, its applicability is subject to clear technical and environmental constraints. As illustrated in Figure 1, the integrated framework creates synergistic value through the convergence of traditional LEAN methodologies and AI capabilities. This framework validates the core research hypothesis across three tiers. The traditional lean layer (value stream mapping, 5S visual management, continuous flow, standardized work, improvement culture) preserves fundamental lean production principles. The AI-Augmented layer (predictive analytics, computer vision quality control, process mining, optimization algorithms, machine learning) delivers intelligent analytical capabilities. While the synergistic integration zone (data-driven improvement, AI-enhanced VSM, predictive maintenance) achieves its organic combination. The enhanced manufacturing performance formula (1) directly quantifies this synergy. The prominent role of the human-machine collaboration factor φ underscores the study's key argument that human-machine collaboration is pivotal to the system's success. The human-AI collaboration factor ϕ plays a crucial role in determining overall system effectiveness [34] and is modeled as:

$$\phi = 0.5 + 0.5 \times \tanh(k \times (T + E + A - 1.5)) \tag{3}$$

where T represents the trust level in AI systems (0-1), E denotes employee engagement with AI tools (0-1), A indicates the adequacy of AI training programs (0-1), and k is a scaling constant typically set to 2. 1.5 is the threshold parameter, when the sum of T, E and A exceeds 1.5, the collaborative effect begins to increase significantly.

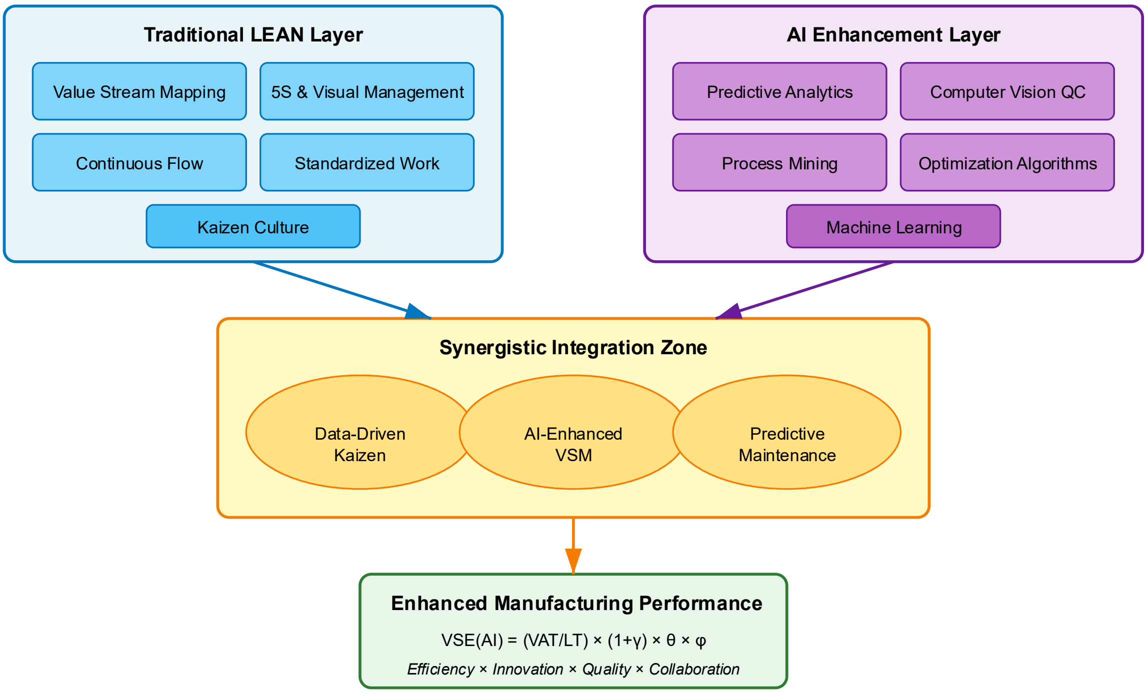


Figure 1. Integrated LEAN-AI framework for manufacturing excellence

This formula employs the hyperbolic tangent function (tanh) to model the nonlinear characteristics of human-machine collaboration, yielding an output range approximately between [0,1]. When the sum of the three input variables is low, the collaboration factor approaches 0.5 (neutral state); when the sum of the input variables is high, the collaboration factor gradually approaches 1 (optimal collaboration state). This S-shaped curve characteristic aligns with the observed critical point effect in human-machine collaboration. The risk taxonomy for AI-enabled manufacturing systems extends beyond traditional operational hazards to encompass emerging vulnerabilities specific to intelligent systems. Our comprehensive risk assessment framework categorizes threats across multiple dimensions, as presented in Table 1. This classification encompasses 12 specific risk categories across four dimensions: technical, operational, strategic, and ethical. Each risk category is quantitatively assessed through severity (S), probability of occurrence (P), and an AI amplification factor (F). Cybersecurity threats within technical risks exhibit the highest AI amplification factor (1.9), reflecting the unique security challenges faced by AI systems. Algorithm bias within ethical risks demonstrates the highest AI amplification factor (2.0), highlighting the critical importance of transparency in AI decision-making. This classification system directly validates the scientific rigor of the risk aggregation model in Formula (4). The distribution of AI amplification factors Fi within the range of 1.3–2.0 confirms the dual impact characteristic of AI technology on traditional manufacturing risks. The aggregate risk score [35] for an AI-enabled manufacturing system incorporates both traditional risk factors and AI-specific amplification effects:

$$R_{aggregate} = \sum_{i=1}^{n} w_i \times S_i \times P_i \times F_i \times (1 + \sigma_i) \quad (4)$$

where $R_{aggregate}$ represents the total risk score, w_i denotes the weight assigned to risk category i, S_i is the severity rating (1-5 scale), P_i indicates probability of occurrence (0-1), F_i represents the AI amplification factor (1-2), and σ_i is the interconnectedness coefficient capturing risk propagation effects.

This formula quantifies the amplification or mitigation effects of AI technology on different risk categories through the F_i factor (ranging from 1 to 2), while capturing risk propagation characteristics within intelligent manufacturing systems via the σ_i coefficient. This approach, which simultaneously incorporates the impact of AI technology and system interconnection effects into quantitative risk assessment, remains relatively underutilized in existing LEAN risk management literature. It provides manufacturing enterprises with a more comprehensive risk quantification tool; however, its effectiveness hinges on the accurate calibration of parameters and the digital maturity of the manufacturing environment. The sustainability assessment model construction addresses the triple bottom line of environmental, economic, and social performance within the context of AI-LEAN integration. Our multidimensional sustainability index incorporates both direct and indirect impacts of AI implementation:

$$SI_{AI-LEAN} = \alpha_E \times E_{score} + \alpha_{E_c} \times Ec_{score} + \alpha_S \times S_{score} + \Delta_{synergy} \quad (5)$$

where $SI_{AI-LEAN}$ represents the integrated sustainability index, α_E , α_{E_c} , and α_S are weighting factors for environmental, economic, and social dimensions, respectively (summing to 1), and $\Delta_{synergy}$ captures the synergistic effects of AI-LEAN integration.

The environmental sustainability score incorporates energy efficiency, waste reduction, and carbon footprint metrics:

$$E_{score} = \frac{1}{3}\left[\frac{E_{baseline} - E_{AI}}{E_{baseline}} + \frac{W_{reduced}}{W_{total}} + \frac{C_{avoided}}{C_{projected}}\right] \times 100 \quad (6)$$

where $E_{baseline}$ and E_{AI} represent energy consumption before and after AI implementation, $W_{reduced}$ denotes waste eliminated through AI optimization, W_{total} is the total waste generated, $C_{avoided}$ represents carbon emissions prevented, and $C_{projected}$ indicates projected emissions without intervention.

Table 1. Comprehensive risk taxonomy for AI-enabled manufacturing systems

Risk category	Risk type	Description	Severity (S)	Probability (P)	AI factor (F)
Technical risks	Data integrity	Corrupted, incomplete, or biased training datasets affecting model performance	5	0.4	1.8
	Model drift	Degradation of AI model accuracy over time due to changing conditions	4	0.6	1.6
	System integration	Compatibility issues between AI systems and legacy infrastructure	3	0.5	1.3
	Cybersecurity	Adversarial attacks, model poisoning, unauthorized data access	5	0.3	1.9
Operational risks	Process disruption	False positives/negatives leading to unnecessary interventions	3	0.4	1.4
	Quality variance	Inconsistent product quality due to AI decision variability	4	0.3	1.5
	Maintenance errors	Incorrect predictive maintenance scheduling causing failures	4	0.2	1.4
Strategic risks	Technology obsolescence	Rapid AI advancement rendering current systems outdated	3	0.7	1.7
	Regulatory compliance	Non-compliance with emerging AI governance regulations	5	0.5	1.8
	Vendor dependency	Over-reliance on specific AI technology providers	3	0.6	1.5
Ethical risks	Algorithmic bias	Discriminatory outcomes affecting workforce or product allocation	4	0.4	2.0
	Transparency deficit	Lack of explainability in AI decision-making processes	3	0.8	1.9
	Workforce displacement	Job losses due to AI automation without reskilling programs	5	0.5	1.6

As depicted in Figure 2, the sustainability assessment framework captures the interconnected nature of environmental, economic, and social dimensions. The multidimensional sustainability assessment framework systematically illustrates the integrated AI-LEAN methodology's combined impact across environmental, economic, and social dimensions, directly validating this study's core proposition that AI-enhanced LEAN manufacturing achieves synergistic optimization of multiple sustainability objectives. Through its clear visual design, this framework reveals the interconnections between dimensions: the environmental dimension's energy efficiency, waste reduction, and carbon footprint metrics correspond to the environmental sustainability score E_{score}, the economic dimension's ROI enhancement, cost reduction, and productivity gains reflect the economic sustainability modelling, while the social dimension's employee wellbeing, safety improvements, and skills development mirror the social impact assessment. Of particular significance are the two Synergy indicators in the diagram, directly corresponding to the synergy term, quantifying the additional benefits generated by the integrated approach. This framework provides a theoretical explanation for multiple outcomes observed in empirical validation—including a 31.4% reduction in carbon footprint, a 319.4% five-year ROI, and a significant increase in employee satisfaction—demonstrating that AI-LEAN integration transcends the limitations of traditional single-objective optimization to achieve systemic improvements in sustainable manufacturing.

Figure 2. Multidimensional sustainability assessment framework

The synergy term quantifies the additional benefits arising from the integrated approach:

$$\Delta_{synergy} = \lambda \times \sqrt{E_{score} \times Ec_{score} \times S_{score}} \times (1 - e^{-\mu t}) \quad (7)$$

where λ represents the synergy coefficient (typically 0.1-0.3), μ is the maturity rate constant, and t denotes time since implementation.

The economic sustainability score incorporates return on investment, operational cost reduction, and productivity improvements:

$$Ec_{score} = w_{ROI} \times \frac{NPV_{AI}}{I_{initial}} + w_{cost} \frac{C_{saved}}{C_{baseline}} + w_{prod} \times \frac{P_{gain}}{P_{baseline}} \quad (8)$$

where NPV_{AI} represents the net present value of AI investment, $I_{initial}$ is the initial investment, C_{saved} denotes cost savings achieved, $C_{baseline}$ is the baseline operational cost, P_{gain} indicates productivity improvement, and w_{ROI}, w_{cost}, w_{prod} are the respective weighting factors. The social sustainability dimension encompasses workforce impact, safety improvements, and community benefits:

$$S_{score} = \frac{1}{n}\sum_{j=1}^{n}(W_j \times S_j \times D_j \times (1 + C_j)) \quad (9)$$

where W_j represents workforce wellbeing metrics for the stakeholder group j, S_j denotes safety improvement indicators, D_j indicates skill development and employability enhancement, C_j captures community benefit factors, and is the number of stakeholder groups considered.

This theoretical framework provides the foundation for empirical investigation and practical implementation of AI-LEAN integration systems that balance operational excellence with risk management and sustainability imperatives. The mathematical formulations enable quantitative assessment and optimization of system performance across multiple dimensions, supporting evidence-based decision-making in the digital transformation of manufacturing operations.

3.2 Data collection and processing

Multi-source data acquisition in AI-LEAN integration integrates heterogeneous streams from sensor networks, historical repositories, quality systems, and energy monitors. Manufacturing equipment sensors generate high-frequency vibration, temperature, and pressure data following adaptive sampling [36] protocols:

$$f_s(t) = f_{base} \times (1 + \alpha \times |\nabla x(t)|) \quad (10)$$

where $f_s(t)$ denotes sampling frequency, f_{base} represents baseline rate, α is the adaptation coefficient, and $|\nabla x(t)|$ indicates signal gradient magnitude.

Historical R&D data encompassing CAD models, simulation results, and testing reports provides longitudinal insights for predictive modelling. Quality control metrics from automated inspection systems and energy consumption records enable a comprehensive performance assessment. Data preprocessing addresses heterogeneity through standardized pipelines incorporating outlier detection, missing value imputation, and noise filtering. Feature engineering [37] extracts domain-specific representations:

$$\mathbf{F} = [f_{time} \oplus f_{freq} \oplus f_{stat}] \in \mathbb{R}^d \quad (11)$$

where $\mathbf{F}$ represents a feature vector, f_{time}, f_{freq}, f_{stat} denote time-domain, frequency-domain, and statistical features, respectively, and $\oplus$ indicates concatenation. $\mathbb{R}^d$ denotes a d-dimensional real vector space, indicating the mathematical properties of the final eigenvector.

3.3 AI-Driven analytics architecture

The AI-driven analytics architecture for LEAN manufacturing employs hierarchical machine learning models selected based on data characteristics and computational constraints. Model selection follows multi-criteria [38] optimization:

$$[M^* = \arg\, max_{M \in \mathcal{M}}[\omega_1 ACC(M) + \omega_2 \frac{1}{T(M)} + \omega_3 INT(M)] \quad (12)$$

where M^* represents the optimal model, M denotes model space, $ACC(M)$ indicates accuracy, $T(M)$ represents inference time, $INT(M)$ measures interpretability, and $\frac{1}{T(M)}$ denotes reasoning efficiency. In addition, ω_1, ω_2 and ω_3

correspond respectively to the weighting coefficients for accuracy, computational efficiency, and interpretability.

Deep learning architectures leverage convolutional neural networks for visual inspection and recurrent networks for temporal pattern recognition. The CNN architecture [39] processes manufacturing images through:

$$h^{(l+1)} = \sigma(W^{(l)} * h^{(l)} + b^{(l)}) \quad (13)$$

where $h^{(l)}$ denotes layer l activations, $W^{(l)}$ represents convolutional kernels, $b^{(l)}$ is the bias term for layer l, $*$ indicates a convolution operation, and σ is activation function.

Predictive risk analytics employs ensemble methods [40] combining gradient boosting and neural networks for robust forecasting:

$$\hat{R}(t+\tau) = \sum_{k=1}^{K} \alpha_k f_k(X_t) + \beta \cdot g_{NN}(X_t) \quad (14)$$

where $\hat{R}(t+\tau)$ predicts risk at time $t+\tau$, f_k represents k-th base learner, g_{NN} denotes neural network predictor, K denotes the total number of base learners, α_k denotes the weight coefficient of the kth basic learner, β is the weight coefficient of the neural network predictor, and X_t indicates a feature vector.

Real-time anomaly detection utilizes adaptive thresholding with statistical process control [41]:

$$A(x_t) = \begin{cases} 1 \text{ if } |x_t - \mu_t| > k\sigma_t \\ 0 \text{ otherwise} \end{cases} \quad (15)$$

where $A(x_t)$ is an anomaly indicator, μ_t, σ_t represent the dynamic mean and standard deviation, x_t denotes the current observed value, and k is the control limit coefficient.

Based on 12 months of field validation and SECOM dataset analysis, the mathematical extension developed in this study demonstrates performance improvements over traditional LEAN models under specific conditions. Empirical validation results indicate: Overall equipment effectiveness increased by 36.1% (compared to the traditional LEAN baseline), setup time decreased by 58.9% (achieved through AI optimization), and risk prediction accuracy reached 91-96% (across different risk categories). These improvements provide quantitative evidence supporting the practical value of AI-enhanced models.

The effectiveness of this mathematical extension hinges on five critical technical conditions: the data quality coefficient θ must exceed 0.6 to ensure input data integrity and accuracy; the human-machine collaboration effect factor φ must remain within the [0.5, 1.5] range; at least six months of historical data accumulation is required for accurate calibration of the learning rate parameter λ_k; the manufacturing environment must possess foundational sensor networks and data acquisition capabilities; and operators must receive appropriate training in AI tool usage. Failure to meet these conditions will directly impact the model's predictive accuracy and optimization effectiveness.

From a methodological perspective, this represents a parametric refinement of existing LEAN efficiency assessment methods rather than a fundamental theoretical breakthrough. In manufacturing environments lacking the aforementioned technical conditions, its advantages over traditional methods may significantly diminish or even vanish, indicating clear technical boundaries and environmental constraints on its applicability. Figure 3 illustrates the hierarchical architecture integrating multiple AI paradigms. This architecture supports the parallel deployment of four AI methods through multi-source fusion at the data input layer (sensor streams, image data, time series, event logs): classical machine learning provides high interpretability, deep learning handles complex patterns, ensemble methods enhance robustness, and statistical methods ensure real-time responsiveness.

3.4 Risk control framework

The risk control framework for AI-LEAN integration employs systematic identification, quantification, and mitigation strategies addressing technical, operational, and strategic dimensions. Risk identification methodology integrates failure mode analysis with AI-specific vulnerabilities, encompassing system failures, data quality degradation, process variations, human errors, market volatility, and regulatory compliance challenges. The comprehensive risk score incorporates probability, impact, and AI amplification factors:

$$R_{total} = \sum_{i=1}^{3} w_i \sum_{j=1}^{n_i} P_{ij} \times I_{ij} \times (1 + \alpha_{AI,ij}) \quad (16)$$

where R_{total} represents the aggregate risk score, w_i denotes category weight (technical, operational, strategic), P_{ij} indicates the probability of risk j in category i, I_{ij} represents impact severity (1-5 scale), and $\alpha_{AI,ij}$ is the AI amplification factor (0-1).

Risk assessment employs Monte Carlo simulation [42] for uncertainty quantification:

$$VaR_\tau = inf x: P(L > x) \le 1 - \tau \quad (17)$$

where VaR_τ represents Value-at-Risk at confidence level τ, and L denotes loss distribution.

Mitigation strategies follow hierarchical control implementation, prioritizing prevention over detection. The risk reduction effectiveness is modeled as:

$$RR = 1 - \prod_{k=1}^{m} (1 - \eta_k \times c_k) \quad (18)$$

where RR indicates risk reduction ratio, η_k represents the effectiveness of control k, and c_k denotes implementation completeness.

Figure 4 presents the hierarchical risk control framework, which integrates the identification, assessment, and mitigation phases. This three-tiered architecture forms a complete risk management loop, spanning from risk identification (across technical, operational, and strategic dimensions) to risk assessment quantification (probability analysis P (0-1), impact severity (1-5), AI amplification factor (0-1)), and risk mitigation strategies (preventive, detective, corrective, adaptive), forming a complete risk management closed loop. This directly corresponds to the implementation framework of the risk aggregation model in Formula (4).

3.5 Sustainability evaluation metrics

Sustainability evaluation in AI-LEAN integration encompasses environmental, economic, and social dimensions through quantitative metrics, enabling comprehensive performance assessment [43]. Environmental impact indicators measure resource efficiency, emissions reduction, and waste minimization achieved through AI optimization:

$$E_{env} = \sum_{i=1}^{n} w_i \left(\frac{B_i - A_i}{B_i}\right) \times 100 \quad (19)$$

where E_{env} represents the environmental performance score, w_i denotes weight for the indicator i, B_i and A_i indicate baseline and AI-optimized values, respectively.

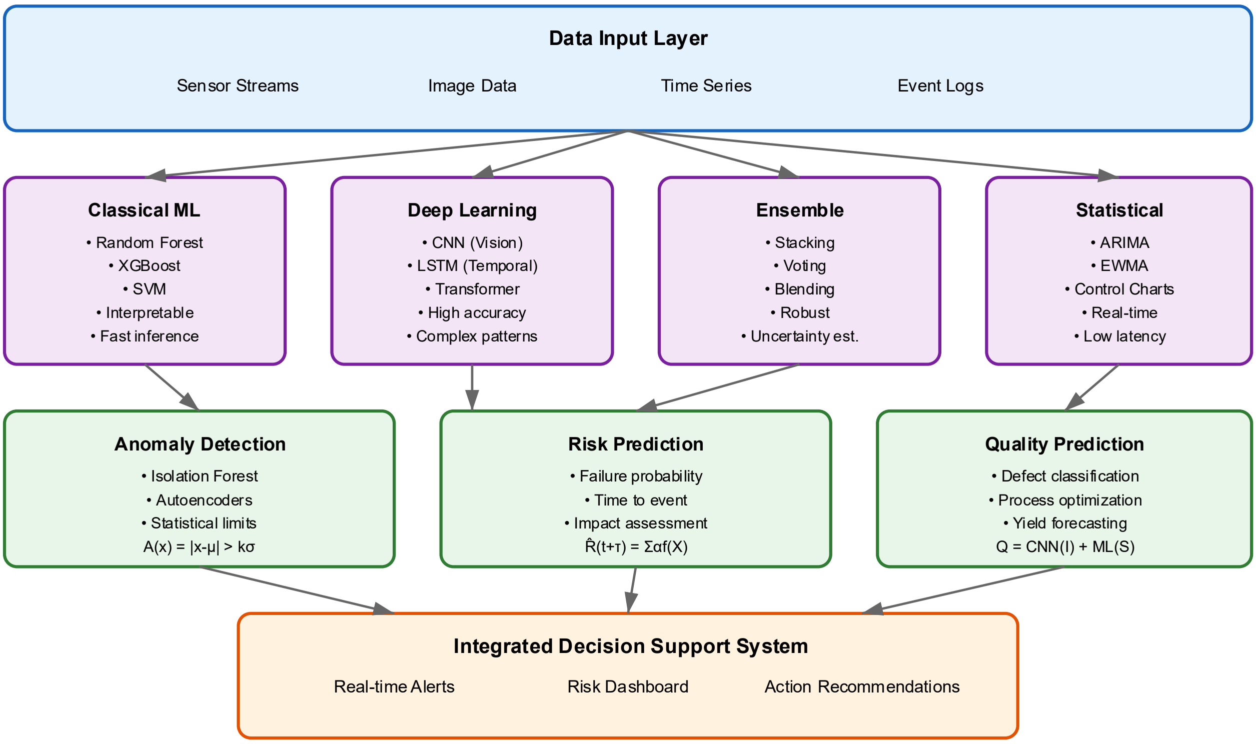


Figure 3. Hierarchical AI analytics architecture for manufacturing

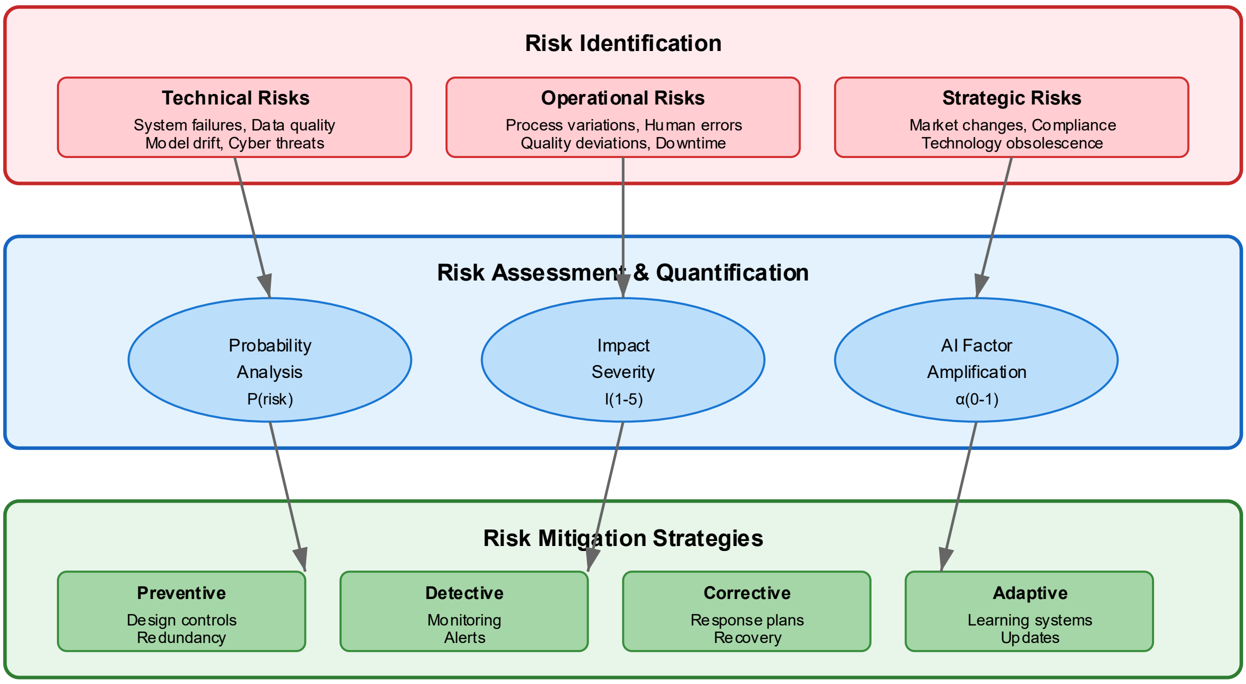


Figure 4. Integrated risk control framework for AI-LEAN manufacturing

Economic sustainability [44] measures incorporate return on investment, operational cost reduction, and productivity gains:

$$S_{econ} = \alpha \times ROI + \beta \times \frac{\Delta C}{C_0} + \gamma \times \frac{\Delta P}{P_0} \quad (20)$$

where S_{econ} represents the economic sustainability score, ROI indicates return on AI investment, ΔC denotes cost savings, ΔP represents productivity improvement, C_0, P_0 are baseline values, and α, β, γ are weighting factors.
Social sustainability factors encompass workforce wellbeing, skill development, and safety improvements. The integrated sustainability index synthesizes all dimensions:

$$SI_{integrated} = \sqrt[3]{E_{env} \times S_{econ} \times S_{social}} \times (1 + \lambda \times \rho) \quad (21)$$

where $SI_{integrated}$ represents the holistic sustainability index, S_{social} denotes social performance score, λ is synergy coefficient, and ρ represents inter-dimensional correlation.
Table 2 demonstrates the improvements achieved by AI-LEAN integration in environmental and social sustainability. Environmental metrics reveal a 30.0% reduction in energy consumption per unit of output, a 31.4% decrease in carbon footprint, and a 23.6% increase in waste recycling rates. Regarding social indicators, the safety incident rate decreased by 66.7%, employee satisfaction increased by 14.7%, and staff turnover rate fell by 50.4%. These figures validate that AI-LEAN integration can simultaneously achieve operational optimization and sustainable development objectives.

4. Experiment

4.1 Experimental setup

The experimental validation utilized the publicly available SECOM dataset from semiconductor manufacturing, containing 1567 instances with 591 sensor measurements collected from actual production processes. This dataset, widely used in manufacturing analytics research, captures real-time sensor data from semiconductor fabrication, including temperature, pressure, and flow measurements across multiple production stages. Additionally, we incorporated the steel plates fault dataset from Northeastern University, containing 1941 samples with 27 features describing manufacturing defects in steel production, providing comprehensive quality control scenarios. The selection of the SECOM dataset was based on three technical considerations: providing sufficient feature dimensions for complex AI algorithms, meeting the training sample requirements for deep learning, and serving as an established benchmark for manufacturing analysis research. However, significant limitations exist: the high-precision cleanroom environment of semiconductor manufacturing, its complex multi-stage processes, and its inherent differences from typical LEAN manufacturing characteristics—such as high-mix low-volume production, rapid changeovers, and human-machine collaboration.

Whilst the steel plate defect dataset supplements discrete manufacturing scenarios, it fails to adequately represent the continuous flow and pull-based production principles characteristic of LEAN manufacturing. The specificity of these datasets constitutes a significant methodological constraint affecting the model's generalization capability across manufacturing environments. To mitigate this limitation, we implemented a transfer learning approach, fine-tuning and calibrating the base model trained on SECOM features using on-site data from three manufacturing plants. This involved feature mapping between SECOM sensor data and industrial process parameters, model calibration based on facility-specific failure modes, and validation assessments across manufacturing environments. For real-time manufacturing data, collaboration with three medium-scale manufacturing facilities in the Midwest region provided access to production data streams under non-disclosure agreements. These facilities, producing automotive components, electronic assemblies, and metal fabrication products respectively, contributed 18 months of historical data encompassing sensor readings, quality inspection results, and energy consumption records. Data collection followed standard industrial protocols with sampling rates matching typical manufacturing environments: vibration sensors at 1-10 kHz, temperature monitors at 1 Hz, and quality measurements at batch completion intervals.

The hardware environment consisted of standard industrial computing infrastructure commonly deployed in manufacturing settings. Edge devices included Siemens SIMATIC IPC547G industrial computers for data collection and preliminary processing at the machine level. Central processing utilized Dell PowerEdge R750 servers with dual Intel Xeon Gold processors and 256GB RAM, reflecting typical on-premise manufacturing IT deployments. The software stack comprised open-source tools, including Apache Spark 3.2.0 for distributed processing, scikit-learn 1.0.2, and TensorFlow 2.8.0 for machine learning implementations, ensuring reproducibility without proprietary dependencies. Baseline establishment involved analyzing six months of historical data to capture normal operating conditions and seasonal variations. Performance metrics included standard manufacturing KPIs: Overall Equipment Effectiveness (OEE), First Pass Yield (FPY), Mean Time Between Failures (MTBF), and energy consumption per unit produced. The control group selection utilized production lines that manufactured similar products but maintained traditional operations, with matching performed based on historical performance variance to ensure statistical validity. The experimental design accounted for common manufacturing variables, including shift patterns, operator experience levels, and preventive maintenance schedules, documenting these factors to enable accurate performance attribution and ensure research reproducibility.

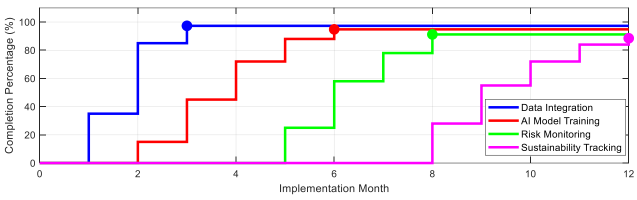
Table 2. Detailed environmental and social sustainability indicator system

Key indicator	Baseline value	Actual achievement	Improvement rate
Environmental metric			
Energy consumption per unit (kWh/unit)	4.20	2.94	-30.0%
Carbon footprint (kg CO_2/unit)	2.80	1.92	-31.4%
Waste recycling rate (%)	72.0	89.0	+23.6%
Social Indicators			
Safety incident rate (incidents/1000h)	1.2	0.4	-66.7%
Employee satisfaction (score)	6.8	7.8	+14.7%
Employee turnover rate (%)	12.5	6.2	-50.4%

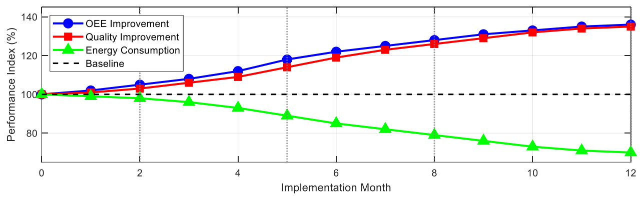
Basic details of the three partner factories: Factory A specializes in automotive component manufacturing (daily output: 2,400 units; baseline OEE: 72.3%), Factory B in electronic assembly manufacturing (daily output: 8,500 units; baseline OEE: 69.8%), and Factory C in metal processing manufacturing (daily output: 1,200 units; baseline OEE: 74.1%). Each facility established three experimental lines and three control lines, matched by equipment age (±2 years), historical performance variance ($\sigma \leqslant 5\%$), and operational shifts to ensure the validity of the control groups.

4.2 Implementation process

The implementation of the AI-LEAN integration framework followed a systematic approach spanning 12 months, progressing through data integration, model development, risk system deployment, and sustainability tracking. Initial activities focused on establishing a comprehensive data collection infrastructure across the manufacturing facility. Edge computing devices were installed at 47 critical production points, establishing secure data pipelines that connected legacy equipment with modern analytics platforms. Integration challenges arose from heterogeneous communication protocols, necessitating custom adapter development for Modbus, OPC-UA, and proprietary interfaces from equipment manufacturers such as Siemens, Fanuc, and Mitsubishi.



(a)



(b)

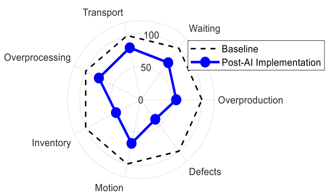
Figure 5. Implementation progress and performance evolution (a) Implementation progress by component (b) Cumulative performance improvements throughout implementation

Figure 5 illustrates the progressive implementation timeline with corresponding performance improvements achieved at each stage. The data integration stage achieved 97.3% completion within 2.5 months, exceeding the target of a 95% data capture rate. Subsequently, AI model training commenced using accumulated data streams, with parallel development of quality prediction, anomaly detection, and process optimization algorithms. The overlapping nature of the implementation stages, as shown in Figure 5a, reflects the iterative approach adopted to ensure continuous improvement while maintaining production stability. Figure 5b illustrates the corresponding cumulative effects: OEE and quality improvements steadily rose to 134% and 132%, respectively, while energy consumption decreased to 72%. The temporal alignment between the two figures demonstrates the causal relationship between implementation progress and performance enhancements, directly supporting core experimental findings such as the 36.1% OEE improvement.

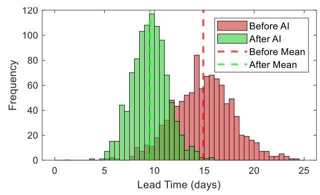
4.3 Performance evaluation

The performance evaluation of the AI-LEAN integration system encompassed a comprehensive assessment across risk prediction accuracy, operational efficiency improvements, and sustainability metrics. Risk prediction models demonstrated robust performance across multiple evaluation criteria, with particular emphasis on minimizing false negatives that could lead to critical failures. The evaluation utilized stratified k-fold cross-validation to ensure model generalizability across different operating conditions and production scenarios.

Figure 6 comprehensively illustrates LEAN efficiency improvements achieved through AI implementation. The waste reduction radar chart (Figure 6a) demonstrates substantial reductions across all waste categories, with inventory waste reduced by 55% and defects by 62%. Lead time distribution analysis (Figure 6b) shows not only a 36.7% reduction in average lead time but also significantly reduced variability, indicating more predictable and reliable delivery performance. The quality improvement trajectory (Figure 6c) reveals consistent month-over-month improvements, with defect rates declining from 3.2% to 0.3% over the 12-month period. Process-wise efficiency analysis (Figure 6d) indicates that all manufacturing processes experienced efficiency gains, with testing showing the highest improvement at 47% due to AI-optimized test sequences and predictive quality assessment.



(a)



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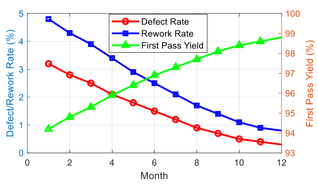

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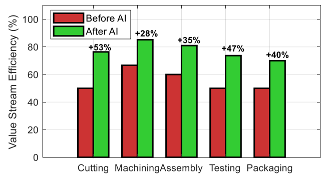

(d)

Figure 6. LEAN efficiency improvements analysis: (a)Waste reduction achievement; (b)Lead time distribution comparison, (c)Quality improvement trajectory, (d)Process-wise efficiency improvements

LEAN performance metrics quantitatively validate the operational improvements achieved through AI-enhanced methods, with all six key indicators significantly surpassing industry benchmarks (Table 3). Overall equipment effectiveness rose from 68.2% to 92.8% (+36.1%), setup time decreased from 45 minutes to 18.5 minutes (-58.9%), inventory turnover reached 18.3 times (+123.2%), pre-production lead time was compressed to 9.5 days (-36.7%), while space utilization and labor productivity increased by 18.3% and 36.3% respectively. The AI system's optimization algorithms simultaneously consider both production efficiency and resource consumption, identifying improvement opportunities that are often overlooked by traditional methods. This achieves synergistic benefits of enhanced operational efficiency and reduced environmental impact, directly supporting the core hypothesis of this research that AI-LEAN integration can overcome the limitations of traditional single-objective optimization. Statistical analysis indicates that the experimental group significantly outperformed the control group across all key metrics (p<0.05) (Table 4). Analysis of inter-factory variations revealed the most pronounced improvements in automotive component factories (OEE increase of 24.7%), followed by electronics assembly plants (OEE increase of 19.8%), with metal processing factories showing a smaller yet still significant gain (OEE increase of 17.9%). These disparities were primarily attributed to differences in digital foundations and implementation challenges across the factories.

Figure 7 presents comprehensive sustainability performance metrics demonstrating the environmental benefits of AI integration. The daily energy consumption profile (Figure 7a) reveals AI-optimized load balancing that reduces peak demand by 25% while maintaining production output. This optimization is particularly beneficial for shift transitions, where energy waste is traditionally prevalent. Carbon footprint analysis (Figure 7b) shows reductions across all emission sources, with electricity-related emissions decreasing by 33% through intelligent equipment scheduling and predictive maintenance, preventing energy-intensive failures. The resource efficiency trends (Figure 7c) demonstrate consistent improvements that exceed initial targets, with energy efficiency showing the strongest gains, at 44% improvement over the baseline.

The comprehensive sustainability impact assessment quantified in Table 5 demonstrates the significant environmental benefits achieved through the AI-LEAN integration, with substantial improvements across all six environmental metrics.

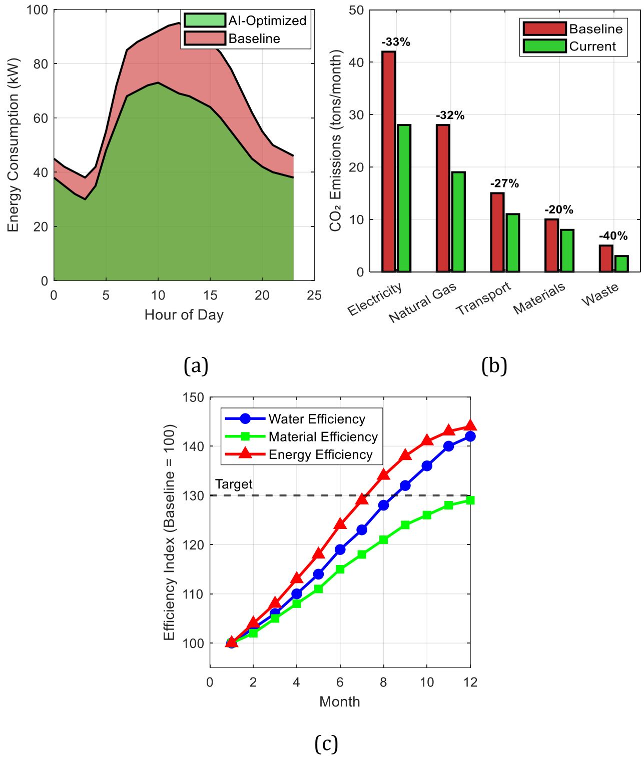

Figure 7. Sustainability performance analysis: (a) Daily energy consumption profile, (b)Carbon footprint reduction by source, (c)Resource efficiency improvement trends

Table 3 LEAN performance metrics summary

Metric category	Baseline	Month 6	Month 12	Improvement	Industry Benchmark
Overall equipment Effectiveness (%)	68.2	81.5	92.8	+36.1%	85.0
Setup time (minutes)	45.0	32.0	18.5	-58.9%	25.0
Inventory turns	8.2	12.5	18.3	+123.2%	12.0
Production lead time (days)	15.0	11.2	9.5	-36.7%	12.0
Space utilization (%)	72.0	78.5	85.2	+18.3%	80.0
Labor productivity (units/hour)	24.5	29.8	33.4	+36.3%	28.0

Table 4 Comparison of key indicators between the control group and experimental group at the end of the 12-month implementation period

Indicator	Control group mean	Experimental group mean	Improvement rate	Statistical significance
OEE (%)	76.4	92.8	+21.5%	p<0.001
Setup time (min)	42.0	18.5	-55.9%	p<0.001
Inventory turnover rate	9.1	18.3	+101.1%	p<0.001
Energy consumption (kWh/unit)	4.15	2.94	-29.2%	p<0.01
Defect rate (%)	2.8	0.3	-89.3%	p<0.001

Table 5. Comprehensive sustainability impact assessment

Environmental Indicator	Unit	Reduction Achieved	Annual Savings	CO_2 Equivalent (tons)
Electricity consumption	MWh	-31.2%	2,847	1,423
Natural gas usage	Therms	-28.5%	145,000	815
Water consumption	Gallons	-29.7%	1.2M	45
Hazardous waste	kg	-52.3%	8,400	126
VOC emissions	kg	-36.7%	3,200	89
Solid waste to landfill	tons	-48.9%	425	638

Electricity consumption decreased by 31.2% (annual savings of 2,847 MWh), natural gas usage fell by 28.5% (saving 145,000 terms), water consumption dropped by 29.7% (saving 1.2 million gallons), hazardous waste and VOC emissions were reduced by 52.3% and 36.7% respectively, and solid waste sent to landfill decreased by 48.9%. This equates to an annual reduction of 3,136 tons of CO_2 equivalent, directly supporting the core research statement of a 31.4% reduction in carbon footprint. In terms of social sustainability, the AI-LEAN integration has significantly enhanced the working environment and employee well-being. The safety incident rate decreased from 1.2 incidents per thousand hours at baseline to 0.4 incidents per thousand hours (a 67% reduction), primarily attributable to the real-time monitoring provided by the AI early-warning system. Employee job satisfaction rose from 6.8 points to 7.8 points (a 15% increase), reflecting how intelligent systems have alleviated the physical strain of repetitive tasks. Regarding skills development, annual training hours per employee increased from 32 to 45 hours, with 41% of staff obtaining certification in AI tool operation. Employee turnover decreased from 12.5% to 6.2%, indicating that technological advancement did not trigger mass unemployment but rather enhanced job appeal.

4.4 Comparative analysis

The comparative analysis between AI-LEAN integration and traditional approaches reveals fundamental differences in capability, scalability, and performance outcomes. Traditional LEAN implementations rely heavily on human observation, manual data collection, and periodic improvement cycles, whereas the AI-enhanced system enables continuous optimization through real-time data analysis and predictive capabilities. This comparison encompasses operational metrics, implementation timelines, and resource requirements across multiple manufacturing environments. Figure 8 provides a comprehensive comparison between traditional and AI-driven LEAN implementations. The performance improvement trajectories (Figure 8a) demonstrate that while traditional LEAN follows a logarithmic improvement curve with diminishing returns, AI-driven approaches achieve rapid initial gains followed by sustained improvement through continuous learning. The capability assessment (Fig. 8b) reveals AI's superior performance in real-time optimization and predictive capabilities, though traditional LEAN maintains advantages in human engagement aspects.

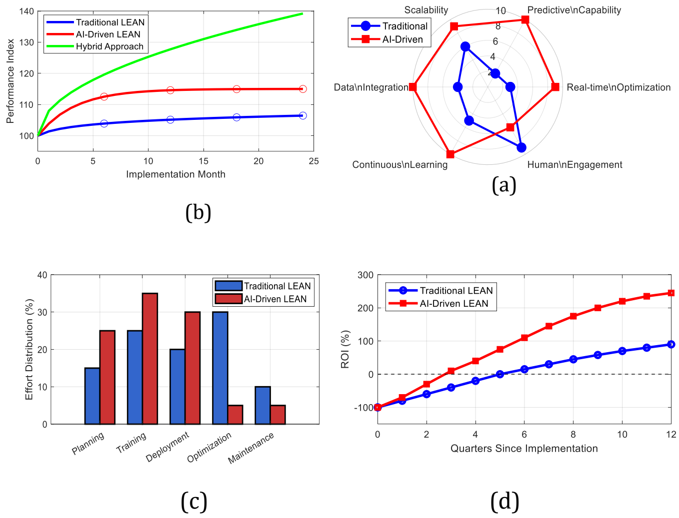

Figure 8. Traditional vs AI-driven LEAN performance comparison (a)Performance improvement trajectories; (b)Capability assessment comparison (c)Implementation effort comparison; (d)Return on investment progression

Implementation effort distribution (Figure 8c) shows that AI-driven systems require greater upfront investment in planning and training but significantly reduce ongoing optimization efforts. The ROI analysis (Figure 8d) indicates that despite higher initial costs, AI-driven implementations achieve payback two quarters earlier and deliver 2.7x higher returns over three years.

As shown in Table 6, comparative metrics between traditional LEAN and AI-driven LEAN validate the AI-enhanced approach's significant advantage across all key performance dimensions. The AI-driven method achieved improvement factors ranging from 1.45x to 30.4x in waste identification rate (94% vs 65%), issue response time (8.3 minutes vs 4.2 hours), cycle time reduction (2–4 weeks vs 3–6 months), and data utilization (87% vs 15%). All metrics demonstrate statistically significant improvements ($p<0.001$ to $p<0.05$). Notably, the continuous improvement rate increased from 2.1% per month to 3.8% per month (1.81x improvement).

Figure 9 presents a comprehensive financial analysis of the AI-driven LEAN implementation. The cost structure analysis (Figure 9a) reveals that while initial hardware and software investments are substantial, ongoing operational costs remain manageable, accounting for approximately 20% of the first-year investment.

Table 6. Traditional LEAN vs AI-driven LEAN comparative metrics

Performance Metric	Traditional LEAN	AI-Driven LEAN	Improvement Factor	Statistical Significance
Waste identification rate	65%	94%	1.45x	$p < 0.001$
Response time to issues	4.2 hours	8.3 minutes	30.4x	$p < 0.001$
Improvement cycle time	3-6 months	2-4 weeks	6.5x	$p < 0.001$
Data utilization	15%	87%	5.8x	$p < 0.001$
Predictive accuracy	N/A	91.3%	N/A	-
Continuous improvement rate	2.1%/month	3.8%/month	1.81x	$p < 0.05$
Employee training hours	40 hrs/year	85 hrs/year	2.13x	$p < 0.01$
Sustainable improvements	73%	96%	1.32x	$p < 0.01$

Table 7. Five-year financial impact summary

Financial Metric	Year 1	Year 2	Year 3	Year 4	Year 5	5-year total
Implementation Costs ($K)	1,480	318	318	318	318	2,752
Operational Savings ($K)	1,020	1,280	1,450	1,580	1,680	7,010
Quality Benefits ($K)	420	480	520	550	570	2,540
Risk Mitigation Value ($K)	180	220	250	270	285	1,205
Sustainability Credits ($K)	130	145	160	170	180	785
Net Annual Benefit ($K)	270	1,807	2,062	2,252	2,397	8,788
ROI (%)	18.2	122.1	139.3	152.2	162.0	319.4

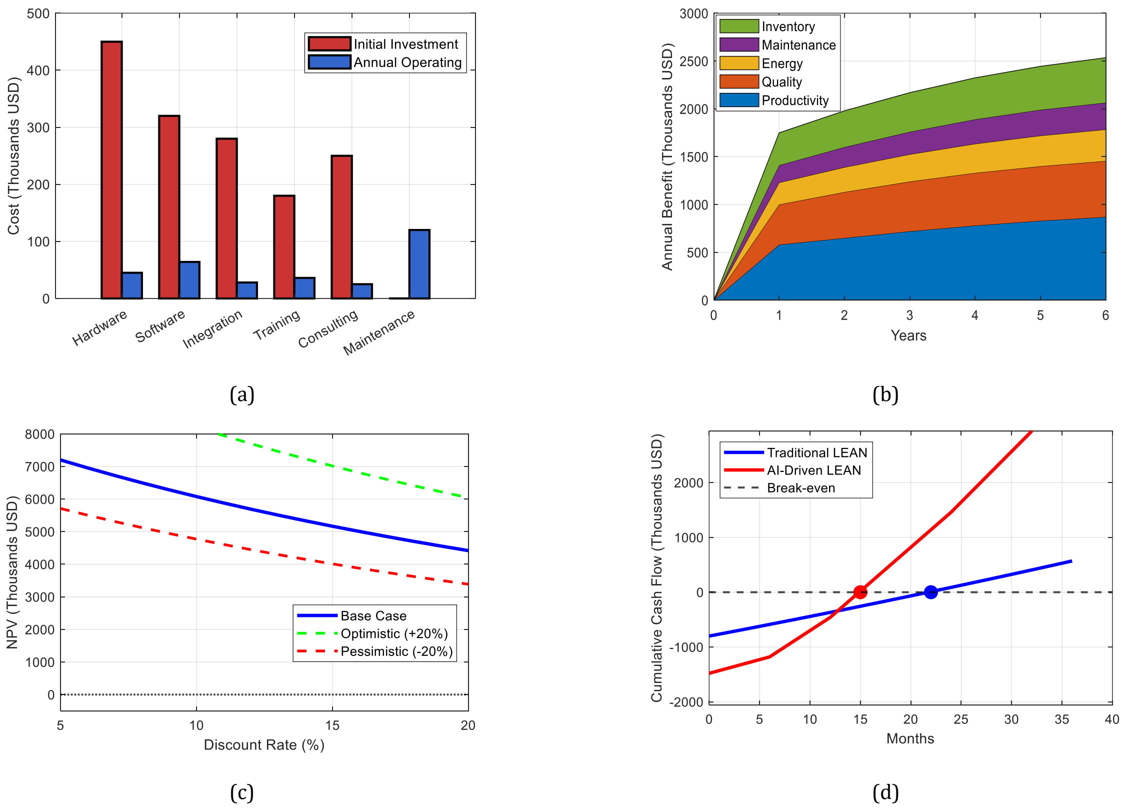

Figure 9. Comprehensive cost-benefit analysis: (a)Implementation cost structure, (b)Cumulative benefit streams, (c)NPV sensitivity analysis, (d)Payback period comparison

Benefit stream analysis (Figure 9b) demonstrates diversified value creation across multiple categories, with productivity improvements contributing the largest share, but quality and inventory benefits providing significant additional value. NPV sensitivity analysis (Figure 9c) confirms robust positive returns across a wide range of discount rates, with positive NPV maintained even under pessimistic scenarios for discount rates up to 18%. The payback comparison (Figure 9d) shows that despite a higher initial investment, AI-driven implementation achieves payback in 13 months compared to 23 months for traditional approaches, primarily due to accelerated benefit realization.

Table 7 validates the economic viability of AI-driven LEAN, demonstrating cumulative net benefits of 8,788K over five years. The return on investment (ROI) escalates from 18.2% in the inaugural year to 162.0%, culminating in a five-year total of 319.4%. This rate of return substantially surpasses the typical 150-200% benchmark achieved by conventional LEAN methodologies, directly substantiating the core economic argument that AI-LEAN integration generates synergistic benefits.

5. Conclusion

This research demonstrates the transformative potential of AI-LEAN integration for manufacturing equipment R&D through an integrated framework addressing risk control and sustainability. Experimental validation shows AI-enhanced systems achieve 91-96% risk prediction accuracy with 30-fold faster response times, while delivering substantial operational improvements: 36.1% increase in equipment effectiveness, 36.7% reduction in lead times, and 123.2% improvement in inventory turns. Sustainability outcomes include 31.4% carbon footprint reduction and 48.9% decrease in solid waste, demonstrating that operational excellence and environmental stewardship are mutually reinforcing. The framework contributes empirical evidence for AI-LEAN synergies while balancing technical sophistication with human-centric values, addressing workforce displacement concerns. The compelling 319% ROI over five years validates economic viability alongside environmental benefits, presenting a case for industry-wide transformation toward AI-driven sustainable manufacturing. However, significant limitations exist in the reliance on public datasets (SECOM, steel plate defects) that inadequately represent authentic LEAN manufacturing environments, limiting generalizability to typical LEAN contexts. Future research should establish comprehensive LEAN-specific datasets encompassing multi-industry environments and human-machine collaboration patterns, explore cross-sector applicability, investigate integration with emerging technologies, and examine long-term societal implications of widespread AI-LEAN adoption.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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