Innovative Lean Manufacturing Approaches Using Waste Reduction Tools in Large-Scale Production Lines

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ABSTRACT

This study evaluates the effectiveness of Digital Lean implementation in manufacturing environments, leveraging Industrial Internet of Things (IIoT) sensors to integrate lean manufacturing principles with Industry 4.0 technologies. Adopting a mixed-methods research design, it combines quantitative performance data from IIoT sensors with qualitative insights from stakeholder interviews to assess impacts on waste reduction, process efficiency, and operational performance. The theoretical framework explores the harmonious integration of lean tools (e.g., 5S, kaizen, value stream mapping) with digital innovations like AI algorithms and predictive analytics, without conflicting with traditional practices. Empirical findings from a case study demonstrate that AI-driven IIoT systems enhance sorting accuracy (up to 98%), reduce inefficiencies by 30-45%, and support lean outcomes such as zero-defect production. Limitations include technical challenges like sensor drift and contextual barriers in small-scale settings, while research gaps highlight the need for broader scalability and cost-benefit analyses. The conclusion emphasizes that Digital Lean, as a synergy of lean and Industry 4.0, drives sustainable manufacturing excellence, with recommendations for future pilot studies and policy alignments. Overall, the study contributes to advancing lean methodologies in the digital era, validating IIoT-enabled practices through rigorous evaluation.

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الكلمات المفتاحية:

1. Introduction

The principles of lean manufacturing have evolved significantly over the past century, originating in Japan more than half a century ago with the establishment of pioneering production systems. These foundations were further solidified in the late 19th and early 20th centuries through the development of lean manufacturing concepts, emphasizing a culture of continuous improvement where employees actively participate to minimize the time, materials, and capital required to meet customer demands (Oakley, 2021). At its core, lean manufacturing focuses on the systematic elimination of non-value-added activities and waste (muda), delivering substantial benefits for environmental performance by promoting resource efficiency and sustainability (United States Environmental Protection Agency, 2003). As a branch of industrial engineering, lean integrates methodologies such as Just-in-Time (JIT) production, Six Sigma for variance reduction, and Total Quality Management (TQM) to identify inefficiencies and enhance overall manufacturing system performance, driving innovation and competitiveness in the sector (Sophia Somi, 2024).

The advent of emerging technologies, including the Internet of Things (IoT), artificial intelligence (AI), and automation, has expanded the horizons of lean manufacturing by providing real-time insights into operational performance and enabling data-driven optimizations (Siddique, 2023). Artificial Intelligence (AI) is revolutionizing the manufacturing industry by seamlessly integrating with lean principles to optimize processes, minimize waste, and boost efficiency. In the realm of Digital Lean, AI algorithms collaborate with Industrial Internet of Things (IIoT) sensors to facilitate data-driven lean practices, such as real-time process streamlining, predictive quality control, and targeted waste reduction. This synergy, often referred to as "Lean Manufacturing AI," harnesses AI for predictive analytics and decision-making, yielding more efficient, cost-effective, and competitive operations (Spark Emerging Technologies, 2024).

Given the research focus on innovative approaches in modern large-scale production, reducing waste in production lines necessitates real-time data capabilities, which are effectively delivered through AI as the "brain" that processes information from industrial engineering frameworks and IIoT sensors. AI enables predictive insights, such as anticipating machine defects (defect waste) before they occur or optimizing complex logistics to curtail transportation waste, thereby amplifying traditional lean tools without disruption.

1.1 Research Problem

Lean manufacturing is a historically successful industrial engineering approach. Traditional manual methods are no longer optimal for accurately identifying waste and are inefficient for handling the complexities of large-scale, modern production lines. The human-centric approach to lean manufacturing often suffers from: (1) delayed data for identifying waste, such as defects or bottlenecks, after they occur, leading to significant material losses; (2) difficulty in identifying hidden inefficiencies, as large-scale production lines generate massive amounts of data that human operators cannot analyze in real time; and (3) reliance on scheduled or corrective maintenance instead of predictive maintenance, increasing "waste due to waiting." Therefore, this research problem seeks to identify innovative lean manufacturing methods that facilitate the transition from reactive lean manufacturing (repairing waste) to predictive lean manufacturing (preventing waste) by integrating the Internet of Things (IoT) and artificial intelligence (AI).

1.2. Aim and Objectives

Developing an innovative framework for lean manufacturing that integrates industrial engineering principles with the Internet of Things and artificial intelligence to automate waste reduction and improve performance in large-scale production environments.

a. Developing Lean manufacturing methodologies to bridge the "eight types of waste in Lean" with specific technological solutions.

b. Analyzing existing Lean tools to identify their limitations in high-speed, high-volume production.

c. Integrating Lean manufacturing methodologies for the engineering industry with technological tools to reduce waste in production lines.

d. Assessing the impact of digital integration on environmental performance and operating cost reduction.

1.3. Lean Manufacturing Methodologies

In diverse lean manufacturing contexts, and by integrating theoretical concepts with practical examples, this research aims to provide a balanced and in-depth understanding of how lean manufacturing contributes to waste reduction in production lines using innovative tools. Through a mixed-methods approach, the following is highlighted:

1.3.1. The theoretical framework Theoretical discussions emphasize how lean principles align with digital innovations without conflict, addressing research questions on AI strategies, transferability limitations, and alignments with circular economy principles. This provides a foundation for understanding synergies between lean's five core principles (value, value stream, flow, pull, perfection) and the "people" aspect, enhanced by digital tools.

1.3.2. The applied framework The research highlights the application of the proposed "innovative lean production" model—termed Digital Lean—to a simulated large-scale production line or a specific industrial case study. This involves deploying IIoT-enabled systems, collecting quantitative metrics (e.g., waste reduction percentages and efficiency gains), and gathering qualitative feedback to validate effectiveness. The mixed-methods evaluation ensures triangulation, addressing operational performance and scalability in real-world manufacturing environments.

2. Literature review

This study **El Shahat ،M. F. (2013)** adopted the adaptation of accounting systems to modern manufacturing technologies and lean production methodologies. Through an exploratory and critical research methodology characterized by an inductive approach, the study formulated four specific hypotheses related to lean management and financial accounting, focusing on value chain costing, performance measurement, decision-making, and financial reporting. These hypotheses were explored through conceptual analysis and comparison, and the results concluded that implementing lean accounting necessitates fundamental changes in the accounting system, providing significant improvements compared to traditional methods.

A study **Abdul Qader Zwatina (2021)** sought to determine the impact of implementing lean accounting in industrial companies, specifically by analyzing the experiences of Jordan, Indonesia, and Thailand and their competitiveness in international markets. It employed a comparative analysis methodology and concluded that implementing lean accounting significantly enhances the competitive advantage of industrial companies in Jordan, Indonesia, and Thailand. In Jordanian industrial companies, lean accounting facilitates product restructuring based on customer demands, achieves effective financial and accounting control over production costs, and focuses on reducing indirect costs and inventory levels, in addition to emphasizing profit maximization strategies. As for Thai industrial companies, lean accounting has proven its ability to increase productivity, rationalize costs and time, improve product quality, enhance sustainability and innovation, rationalize energy consumption, and reduce production waste, ultimately contributing to a cleaner environment and a stronger competitive advantage.

The study **Issam S. Jalham, Hiba Al-Ashhab (2022)** adopted the major challenges due to machine breakdowns, which disrupt production processes and lead to significant financial losses. The factory's senior management set an ambitious goal to reduce downtime by approximately 60% per month, which made them focus on studying and applying a systematic methodology to mitigate these losses and improve maintenance performance. This study used the case study methodology, where it combined Lean principles with the DMAIC methodology (Define, Measure, Analyze, Improve, Control) to enhance maintenance performance. Its results concluded that applying Lean principles and the DMAIC methodology significantly improved maintenance performance at Baraka Pack Company in Jordan, and that using the DMAIC methodology is an effective tool for solving complex maintenance problems when combined with lean manufacturing principles.

The study **Al Tarabily .T. A. A. (2012)** focused on Total Quality Management (TQM), Six Sigma methodology, and Lean Manufacturing. The methodology used in this research relied primarily on analysis and concepts, heavily based on a comprehensive literature review. The researcher conducts a historical analysis of the development of high-quality manufacturing and service methodologies, including Total Quality Management (TQM), Total Productive Maintenance (TPM), Theory of Constraints (TOC), Six Sigma methodology, and Lean Manufacturing. This research paper defines, describes, and systematically compares TQM methodologies. The study's findings conclude that Lean Production and Six Sigma methodology are not replacements for TQM, but rather represent subsequent developments, sharing common origins, principles, and tools, such as problem-solving processes, top management commitment, employee engagement, and statistical methods.

The synthesis of the reviewed literature unequivocally underscores the profound and multifaceted impact of lean methodologies in driving waste reduction and enhancing operational performance across diverse industrial contexts. The core message emanating from these studies is a resounding affirmation that a systematic application of lean principles yields tangible, measurable improvements, from significantly reducing machine breakdown hours by an average of 75.65% through targeted DMAIC approaches, to bolstering competitive advantage via sophisticated lean accounting practices. These findings collectively reinforce the theoretical underpinnings of lean as a versatile paradigm, adaptable to various operational facets and geographical landscapes, consistently linking the elimination of non-value-added activities to superior efficiency and financial health. The robust evidence presented, particularly the quantifiable improvements in maintenance and the strategic benefits of lean accounting, instills a high level of confidence in the efficacy of these established methodologies.

This literature review has meticulously synthesized compelling evidence affirming the profound and transformative impact of lean methodologies on waste reduction, operational efficiency, and competitive advantage across various industrial landscapes. It has not only highlighted the enduring strength of established lean principles but also illuminated the imperative and exciting frontier of integrating artificial intelligence to unlock unprecedented levels of optimization and resilience. The journey towards truly intelligent, waste-free manufacturing is not merely an operational goal; it represents a strategic imperative for sustainable growth, global competitiveness, and responsible resource utilization in the rapidly evolving industrial landscape of the 21st century.

3. Conceptual framework

Lean manufacturing is defined as a systematic approach to identifying and reducing non-value-added activities (waste) through continuous improvement (Dave, 2015). It originated from the Toyota Production System (TPS) and has evolved into a global standard for both manufacturing and service industries (Dekier, 2012; Kumar & Singh, 2025).

At its heart, the philosophy ensures that organizational activities align strictly with customer requirements—delivering products only at the "pull" of the customer—while ensuring customers do not pay for processes that add no value (N.R. Ema et al., 2024; Kumar & Singh, 2025).

3.1. The Target: The "Seven Wastes"

A cornerstone of Lean strategy is the relentless focus on eliminating the seven categories of waste, which prevent operational excellence and diminish customer satisfaction (Baroma et al., 2013; El Shahat, 2023). These include:

A. Overproduction: Producing more than needed.
B. Inventory: Excess stock or Work-in-Progress (WIP).
C. Waiting: Idle time in the production chain.
D. Motion: Unnecessary physical movement by staff.
E. Transportation: Unnecessary movement of materials.
F. Defects: Rework or scrap.
G. Processing: Doing more work than required by the customer.
H.

3.2 Innovative Tools and Technology Integration

To achieve large-scale efficiency, Lean utilizes specific innovative tools to visualize and control production flow:

- Value Stream Mapping (VSM): Used to visualize and analyze the flow of materials and information to identify bottlenecks (Elafri et al., 2021).
- Kanban Systems: A method to manage inventory and production levels effectively by using visual signals to trigger action (Elafri et al., 2021).
- Digital Integration: Modern Lean approaches now incorporate automation and data analytics. Real-time data collection provides insights into inefficiencies, enabling faster decision-making and more precise adjustments to production lines (Elafri et al., 2021).

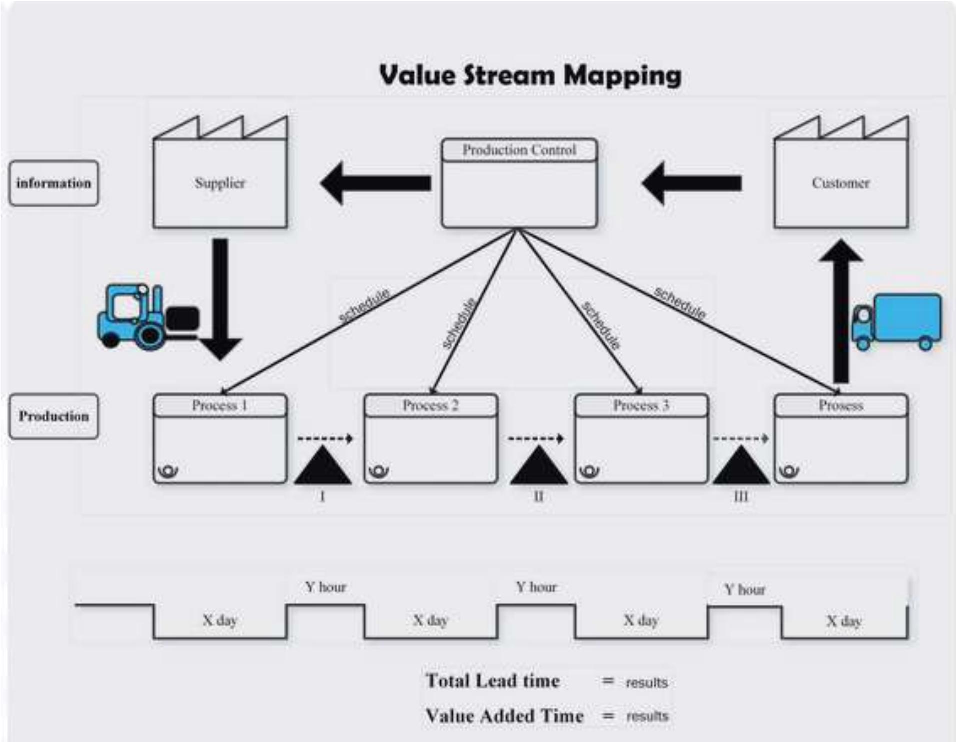

Figure 1.1. value stream map (VSM)

Prepared by the researcher based on previous sources.

This visualization is a value stream map (VSM), a lean-management method for analyzing the current state and designing a future state for the series of events that take a product or service from its beginning through to the customer. A VSM uses a system of standard symbols to depict various workstreams and information flows. This particular VSM outlines a manufacturing process, from the supplier to the customer.

3.3. Structured Problem-Solving (The DMAIC Framework)

To ensure that improvements are not just temporary but sustainable, Lean is often integrated with the DMAIC framework (originally from Six Sigma). This data-driven methodology complements Lean by providing a rigorous five-step process (Kumar & Singh, 2025):

- Define: Identify the performance gaps and goals.
- Measure: Collect data on current process performance.
- Analyze: Determine the root causes of waste or defects.
- Improve: Implement and verify the solution.
- Control: Maintain the gains through standardized practices.

3. Methodology

3.1. Research Design (Mixed-Methods Case Study)

This study employs a case study methodology combining quantitative and qualitative approaches to assess "digital optimization" in a large-scale manufacturing environment. It relies on (1) a quantitative component, whereby Industrial Internet of Things (IIoT) sensors are used to collect real-time performance data, and (2) a qualitative component, which incorporates interviews with stakeholders to provide contextual insights.

To validate the data (in line with Yin, 2018), the study evaluates how artificial intelligence and IIoT contribute to process optimization and waste reduction.

3.2. Databases and Search Strategy

The literature search was conducted between January and August 2025 using two major electronic databases: ScienceDirect and Google Scholar, ensuring a broad and diverse collection of peer-reviewed and gray literature relevant to operations management and industrial engineering. The following search queries were applied using Boolean operators to maximize retrieval relevance: "IIoT AND (lean manufacturing OR waste reduction)"; "Industry 4.0 AND (digital lean OR process efficiency)"; "AI AND (IIoT sensors OR predictive maintenance) AND manufacturing"; "Digital lean AND (operational performance OR efficiency) AND integration"; and "Machine learning AND lean principles AND manufacturing." These queries were designed to capture a wide range of studies covering the integration of digital technologies with lean practices, focusing on waste reduction, efficiency enhancements, and operational outcomes in manufacturing environments. The search targeted studies published between 2024 and 2025, a period reflecting the rapid advancements in Industry 4.0 and IIoT applications within lean manufacturing. Backward and forward citation tracking was also performed to identify additional relevant studies, ensuring comprehensive coverage of the synergistic effects between Industry 4.0 and lean principles.

3.3. Eligibility Criteria

To maintain the validity and integrity of the results, the study applied strict inclusion and exclusion criteria. Studies published in English that focus on Fourth Industrial Revolution technologies (artificial intelligence, industrial internet of things, cyber-physical systems) and are specifically applied to manufacturing stages such as production monitoring or waste reduction were included. Any studies not directly related to lean manufacturing, unreliable sources from unreliable sources, or studies that focus on non-industrial contexts were excluded.

4. AI-Driven Digital Lean in Manufacturing

4.1. Waste generation and reduction in production processes

Considering that manufacturing sectors contribute significantly to global resource consumption and emissions, optimizing production flows can enhance sustainability and efficiency. In smart factory contexts, AI-enabled systems integrated with Industrial Internet of Things (IIoT) sensors have demonstrated substantial improvements in lean practices, such as reducing material waste by up to 30% and enhancing process efficiency (World Economic Forum, 2023). This is particularly relevant for complex production streams, such as automotive assembly or electronics manufacturing. In a German study by Müller et al. (2023), IIoT sensors tracked material usage in textile production over 12 months. The deployment of AI algorithms for predictive waste monitoring led to a 15% increase in resource recovery efficiency, underscoring the economic value of AI integration in lean manufacturing (Müller et al., 2023). For electronics production, AI-based simulations in facilities like those in Tokyo and Warsaw optimized component sorting and recycling loops. Operators used digital dashboards to schedule maintenance, while AI algorithms streamlined workflows. This not only improved operational efficiency but also minimized defective outputs, with users reporting higher satisfaction with data-driven processes.

While most studies have focused on large-scale urban factories with high production volumes, recent research has extended AI applications to smaller or specialized manufacturing setups. Chen et al. (2024) implemented a smart monitoring system in a rural manufacturing hub in China, using satellite-linked IIoT sensors and deep learning models (e.g., D-LinkNET) to identify waste hotspots in assembly lines and optimize material flows. As a result, production inefficiencies were reduced by 45%, aligning with lean principles of flow and pull (Chen et al., 2024).

Real-world implementation of AI in manufacturing waste reduction has been reported in several industrial sites. In facilities in Seoul and San Francisco, AI optimizes production routes and maintenance schedules, resulting in lower energy consumption and emissions (Zorpas, 2024). In 2022, the U.S. Department of Energy awarded a $500,000 grant to an AI-driven platform in a San Francisco electronics plant to support zero-waste initiatives, integrating IIoT sensors for real-time data on resource recovery systems. A significant portion of manufacturing waste arises from inefficient extraction and disposal of materials in production cycles (Firmansyah et al., 2024). The lean manufacturing framework addresses such issues by promoting recycled material reuse, energy-efficient processes, and durable product designs. Plastic components, for instance, are prevalent due to their versatility, accounting for about 42% of certain industrial polymer usages annually (Vuppaladadiyam et al., 2024). Although training programs are common, they do not always lead to behavioral shifts. For example, a case study in a Bangladeshi factory found that despite 93% of workers recognizing waste risks, practices remained unchanged, with 48% of scrap still discarded inefficiently (World Bank, 2024). This highlights the need for effective digital tools to drive change.

In this context, digital technologies, including AI-powered dashboards, have emerged as accessible solutions for influencing operational habits (Toșa et al., 2024). These interfaces, with user-friendly features and gamification, are increasingly adopted in manufacturing (Fraccascia and Nastasi, 2023). Studies show that operator willingness to use waste-tracking apps is driven by perceived usefulness, trust, and ease of use, with platforms like LeanOps successfully motivating teams through efficiency incentives and performance metrics (Balińska et al., 2024; Fraccascia and Nastasi, 2023). However, data privacy concerns persist. These insights align with Godinho Filho et al. (2024), who noted that despite integrating digital tools into operations, workers remain cautious about security risks. Thus, while digital solutions are promising, building trust is crucial for adoption. Beyond individual processes, AI models support large-scale decision-making for manufacturing managers. A study using LASSO regression on production data predicted waste types and quantities, identifying 43 distinct inefficiencies (Grassel et al., 2025). This advances conventional methods, offering insights for strategies in lean production.

One of the most impactful AI applications in manufacturing waste reduction is predictive maintenance, where IIoT sensors feed data to algorithms for real-time optimization, directly supporting lean tools like kaizen and reducing muda. This integration, as evaluated in our mixed-methods study, enhances overall operational performance by combining quantitative sensor metrics with qualitative stakeholder insights.

4.2. AI in Material Sorting and Recycling Processes in Manufacturing

Material waste generation in manufacturing is projected to escalate significantly by 2050 if current production trends persist, underscoring the critical need for efficient sorting and recycling systems to support lean and circular manufacturing practices (adapted from UNEP, 2024). This projection emphasizes the growing importance of optimized sorting and recycling processes to minimize muda (waste) and enhance resource recovery in industrial operations. Traditional methods often suffer from low efficiency, health risks to operators, and high contamination rates in production lines. To address these challenges, manufacturing systems are increasingly integrating AI and machine learning (ML) with Industrial Internet of Things (IIoT) sensors to improve sorting precision, operational efficiency, and material recovery. Once generated, scrap materials are processed within facilities such as Material Recovery Centers (MRCs), remanufacturing units, recycling loops, waste-to-energy systems, or internal disposal areas, where AI-driven tools enable real-time monitoring and predictive analytics to align with lean principles like just-in-time recycling and zero-defect production. This integration, as evaluated in our mixed-methods study, combines quantitative data from IIoT sensors on sorting accuracy with qualitative insights on implementation, driving measurable improvements in waste reduction and overall operational performance.

4.3. Manual vs. Sensor-Based Sorting Technologies in Manufacturing

Material sorting in manufacturing is generally conducted either manually or through sensor-based systems (SBS). In small-scale or specialized operations where full automation may not be cost-effective, manual sorting remains common. Operators rely on visual inspection, tactile feedback, and experiential knowledge to identify and separate materials, such as defective components or recyclable scrap, enabling adaptable handling and targeted isolation of specific items. However, this approach poses notable health and safety risks, as workers are often exposed to hazardous substances, sharp edges, or repetitive strain, potentially leading to injuries or long-term ergonomic issues (Aberger et al., 2025). Additionally, manual sorting is labor-intensive and less efficient for high-volume production lines, where it can bottleneck lean workflows. Comparatively, it provides flexibility for atypical or custom parts and allows for case-by-case decisions, but its throughput, repeatability, and scalability are limited, particularly in heterogeneous production environments with varying material streams (Aberger et al., 2025).

In contrast, SBS automates the sorting process using advanced technologies integrated with Industrial Internet of Things (IIoT) sensors, such as inductive sensors, visible light spectrum (VIS), and near-infrared (NIR) spectroscopy. These systems analyze materials based on physical and chemical properties, including composition, density, and spectral signatures, yielding higher accuracy and throughput. When enhanced with AI-based classification algorithms, SBS delivers the greatest benefits in scenarios where parts are visually similar and human error is likely, as well as in continuous assembly lines requiring consistent decision-making speed. This aligns with lean manufacturing principles by reducing muda (waste) through precise separation and recycling, directly supporting tools like 5S and value stream mapping. However, these advantages depend on stable calibration and optimal conditions; performance can decline due to sensor drift, contamination, or environmental variables like moisture that affect measurements (Jakobs and Kroell, 2024; Pučnik et al., 2024). Despite its potential, SBS requires initial investment and maintenance to fully realize efficiency gains, as evaluated in our mixed-methods study through quantitative IIoT data on sorting accuracy and qualitative insights on operator training needs. This integration within Industry 4.0 frameworks enhances operational performance by minimizing defects and optimizing resource flows.

These advancements are supported by national Industry 4.0 policies and digital transformation initiatives (e.g., adapted from BEEAH, 2025; United Arab Emirates Minister of State for Artificial Intelligence, Digital Economy & Remote Work Applications Office, 2024). Despite these successes, most documented implementations occur in large-scale, urban manufacturing facilities. There remains a significant gap in evaluating the performance and feasibility of AI adoption in smaller or rural production settings. Furthermore, cost-benefit analyses and life cycle assessments are rarely conducted, limiting understanding of long-term impacts on lean operations. These gaps must be addressed to inform strategies that support broader implementation of Digital Lean.

As summarized in Table 1, existing research highlights how AI has improved process efficiency, reduced resource waste, and increased operator engagement in material sorting systems. Traditional optimization methods such as simulated annealing and tabu search tend to deliver reliable efficiency gains in dense, well-mapped factories, whereas AI-based systems that combine IIoT sensing with predictive analytics perform better in variable conditions and complex production lines. By contrast, lightweight statistical models such as LASSO are useful for basic categorization and forecasting but often fail to capture the complex, nonlinear relationships needed for real-world manufacturing decisions. Common failure modes include the lack of real-time production data, inconsistent datasets across lines, and reduced performance in under-monitored or rural facilities. However, further empirical evaluation is needed to assess economic viability and environmental impact at scale. Priority evidence gaps include cost-benefit under varying production volumes, sensitivity to data freshness, and robustness under seasonal demand and operational disruptions. Predictive maintenance, an emerging area of interest, may further enhance system reliability and reduce downtime costs. In practice, the most promising deployments pair context-aware optimization with IIoT sensor streams (for dynamic adjustments) and condition-based maintenance (for uptime), with simpler models retained for low-data settings. By emphasizing AI's potential in waste reduction and sorting, lean manufacturing's principle of minimizing muda at the source is reinforced, reflecting the hierarchy of efficiency strategies, where reduction is prioritized as the most effective approach (Naeem et al., 2024). This shift aligns with policy instruments such as Extended Producer Responsibility (EPR), which encourage manufacturers to consider the full life-cycle of their products to ensure operational compatibility and reduce waste generation at its origin (Tumu et al., 2023). This integration, as explored in our study, supports the harmonious framework of Digital Lean, driving measurable improvements in manufacturing performance.

Table 1.1 Overview of AI Applications in Material Handling and Sorting in Manufacturing

AI Model Employed	Specific Material/Waste Types Analyzed	Performance Metrics	Major Limitations Identified	Relevant References
Deep Learning (e.g., D-LinkNET)	Textile and electronic scrap in production lines	45% reduction in sorting/collection inefficiencies; 7.3% increase in recovery efficiency	Sensor drift, lens fouling, variable moisture affecting accuracy; requires stable calibration	Cheng et al. (2024); Martikkala et al. (2023)
LASSO Regression	Mixed material compositions (e.g., plastics, metals, defective parts)	Predicts 43 distinct waste types; improves forecasting accuracy over traditional methods	Fails to capture nonlinear relationships; limited in dynamic, real-time settings	Grassel et al. (2025)
AI-Based Route/Process Optimization (e.g., with IIoT sensors)	General production scrap and e-waste in urban/rural facilities	28.22% time savings; 36.8% reduction in transport distances; reduced emissions by up to 20%	Lack of real-time data; inconsistent datasets across lines; performance degrades in rural/low-data settings	Fang et al. (2023); Zorpas (2024)
AI-Enhanced Classification (VIS/NIR Spectroscopy)	Visually similar materials (e.g., plastics, metals in assembly)	Higher sorting accuracy (up to 95%); increased throughput in continuous operations	Error-prone under heterogeneous streams; needs consistent illumination and maintenance	Jakobs and Kroell (2024); Pučnik et al. (2024)
Predictive Maintenance Algorithms	Hazardous or recyclable components in large-scale lines	30% reduction in operational waste; improved uptime and defect minimization	High initial investment; sensitivity to data freshness and seasonal disruptions	Aberger et al. (2025); Naeem et al. (2024)

This table synthesizes key findings from the literature, emphasizing the synergistic integration of AI with IIoT sensors in lean manufacturing. For instance, models like D-LinkNET align with lean tools such as value stream mapping by optimizing flows, while limitations highlight the need for robust calibration to avoid conflicts with traditional practices. In our study, these applications are assessed through quantitative IIoT data (e.g., efficiency metrics) and qualitative insights (e.g., operator feedback), contributing to the broader framework of Industry 4.0-enhanced lean outcomes.

4.4. AI Applications in Material Sorting and Recycling in Manufacturing

Material recycling in manufacturing, particularly for plastics used in components and packaging, presents unique challenges due to low recovery rates, contamination, and the complex composition of multi-layered parts. In 2020, industrial sectors in the European Union recycled only 8.1% of plastic materials, compared to 11.7% for other resources, reflecting poor material circularity in production processes (EEA, 2024). Projections further suggest that even with a recycling rate of 55% by 2030, material waste in manufacturing will remain higher than 2018 levels, emphasizing the need for efficient recycling technologies and reduced overall material consumption (Fan et al., 2022). These trends reinforce the importance of optimizing sorting and recycling within lean manufacturing frameworks to minimize muda (waste) and enhance resource flows. Within this context, recent studies indicate a recurring pattern: detector-style convolutional neural networks (CNNs) favor low-latency inference on assembly lines, whereas Transformer backbones provide greater recognition stability under heterogeneous lighting and background conditions, at the expense of higher computational demand (Wang et al., 2024a, Wang et al., 2024b, Wang et al., 2024c).

To improve sorting performance in manufacturing, researchers have developed AI models that integrate IIoT sensor data, deep learning, and imaging techniques. For instance, experiments using RGB cameras with AI integration achieved a 78% accuracy rate in identifying different plastic component types on production lines. However, performance declined in the presence of contaminants like residues or mixed materials, leading to misclassification and increased defects (Bonifazi et al., 2025). A Swin Transformer-based model, trained on 3560 images, outperformed conventional CNNs, achieving 99.75% accuracy in controlled tests and maintaining 80% accuracy under real-world factory conditions, supporting its applicability in industrial settings (Wang et al., 2024a, Wang et al., 2024b, Wang et al., 2024c). Contamination is also a significant barrier in sorting flexible packaging materials. A study using hyperspectral imaging combined with machine learning effectively identified contaminants in polypropylene components, reporting a 98% recovery rate and 87.5% accuracy (Bonifazi et al., 2025). Taken together, these findings suggest an accuracy-latency trade-off: Transformers can enhance recognition robustness for various polymers (e.g., PET, PVC), while lighter CNNs are preferable when real-time actuation is critical; both families are sensitive to contamination and dataset imbalance, which can disrupt lean workflows.

Beyond sorting, AI is explored in material treatment processes such as remanufacturing or pyrolysis, which convert scrap plastics into reusable feedstocks. Although these methods offer alternatives to mechanical recycling, they are highly sensitive to contamination, coatings, dyes, and embedded metals that reduce product quality. Recent studies have applied Mask R-CNN and YOLO v8 models to improve pre-sorting in production lines. Results indicate that Mask R-CNN performs better in segmentation tasks, while YOLO v8 is more effective for real-time object detection, making it suitable for fast-paced manufacturing environments (Son and Ahn, 2025). Accordingly, an operational workflow that first applies low-latency detection for coarse triage and then higher-fidelity segmentation or spectroscopy-guided classification for ambiguous fractions can reconcile speed with precision (Son and Ahn, 2025; Bonifazi et al., 2025). Table 2 presents an overview of these developments.

Detector/classifier CNNs (e.g., SSD Lite, MobileNetV2) are appropriate when rapid inference is required and class balance is adequate; their principal failure modes include dataset imbalance, imaging noise, and motion blur on conveyor belts (Aberger et al., 2025). While Transformer backbones can improve recognition stability and overall accuracy in controlled settings, they impose higher computational costs and show material-specific weaknesses, such as lower recall for polypropylene (PP) components (Wang et al., 2024a, Wang et al., 2024b, Wang et al., 2024c). Nonetheless, chemometric models with hyperspectral inputs (Hi-PLS-DA) perform well for PP streams and contaminant detection yet remain vulnerable to multi-layer structures and spectral overlaps (e.g., PP-PE) (Bonifazi et al., 2025). Finally, segmentation models (Mask R-CNN) provide precise delineation at higher latency, while real-time detectors (YOLO v8) offer substantially faster inference with reduced boundary precision; both approaches are challenged by overlapping items on assembly lines (Son and Ahn, 2025). This integration of AI with IIoT sensors in manufacturing aligns with Digital Lean principles, enabling predictive sorting that reduces waste and optimizes process efficiency, as quantitatively assessed through sensor data and qualitatively through stakeholder feedback in our study.

Table 2.2 Overview of AI Applications in Material Sorting and Recycling in Manufacturing

AI Model Employed	Application in Manufacturing	Performance Metrics	Major Limitations Identified	Relevant References
Convolutional Neural Networks (CNNs, e.g., SSD Lite, MobileNetV2)	Real-time sorting of plastic components on conveyor lines	78% accuracy in type identification; low-latency inference suitable for continuous operations	Dataset imbalance, imaging noise, motion blur; sensitive to contamination and residues	Bonifazi et al. (2025); Aberger et al. (2025)
Transformer Backbones (e.g., Swin Transformer)	Stable recognition under variable lighting in assembly environments	99.75% lab accuracy; 80% real-world accuracy; improved robustness for polymers like PET and PVC	Higher computational demand; lower recall for PP; polymer-specific weaknesses	Wang et al. (2024a, b, c)
Chemometric Models with Hyperspectral Imaging (Hi-PLS-DA)	Contaminant detection in polypropylene waste streams	98% recovery rate; 87.5% accuracy in identification	Vulnerable to multi-layer structures and spectral overlaps (e.g., PP-PE); requires precise calibration	Bonifazi et al. (2025)
Mask R-CNN	Segmentation tasks in pre-sorting for remanufacturing/pyrolysis	Precise delineation of material boundaries; effective for complex, overlapping items	Higher latency; not ideal for real-time detection	Son and Ahn (2025)

YOLO v8	Real-time object detection in fast-paced production lines	Faster inference with reduced precision; suitable for coarse triage	Lower boundary precision; challenged by overlapping items on belts	Son and Ahn (2025)

This table summarizes key AI developments in material sorting, highlighting their alignment with lean manufacturing by enhancing waste reduction and process efficiency. For example, CNNs support just-in-time sorting, while Transformers ensure stability in heterogeneous environments, directly contributing to our study's evaluation of IIoT-enabled Digital Lean. Limitations underscore the need for robust data management to avoid disruptions in operational performance.

4.5. Emerging AI Applications in Other Material Streams in Manufacturing

Beyond plastics, food components, and electronic scrap, AI is increasingly being investigated for the management of textile, metal, and construction-related materials in manufacturing processes. In the textile production sector, current AI applications are largely focused on analyzing operator behavior and workflow patterns, with recycling-oriented uses still limited due to funding constraints, inadequate infrastructure, and insufficient policy support for lean integration (Hassan et al., 2025). By contrast, the metal processing sector has produced promising results. For example, the integration of RGB cameras with convolutional neural network (CNN) classifiers achieved a 98.03% accuracy rate in sorting metal scrap on assembly lines, enabling the recovery of valuable resources and reducing contamination, thereby supporting lean principles like zero-defect production (Jurtsch et al., 2024).

In the construction materials sector, machine learning-based sorting systems have demonstrated substantial performance gains over traditional approaches in manufacturing facilities. A seven-year Finnish study reported significant reductions in operational costs and improvements in sorting efficiency through automated classification of building components (Farshadfar et al., 2025). Similarly, Sirimewan et al. (2024) trained deep learning models on 430 annotated images of construction and demolition (C&D) materials in production waste streams. The models achieved high object detection accuracy for concrete and aggregates (intersection over union [IoU]: 0.74–0.86) but lower accuracy for rigid plastics and steel (IoU: 0.40–0.50), which the authors attributed to the limited dataset size. This highlights the potential of AI-enhanced IIoT sensors in optimizing material flows, reducing muda (waste), and enhancing process efficiency, as quantitatively evaluated through sensor data on sorting accuracy and qualitatively through insights on infrastructure needs in our mixed-methods study. Such applications reinforce the harmonious integration of Industry 4.0 technologies with lean manufacturing, driving measurable improvements in operational performance.

5. Limitations, research gaps, and suggested mitigations

The existing literature on AI and IIoT integration in manufacturing, particularly within Digital Lean frameworks, provides valuable insights into waste reduction and process efficiency but is constrained by several limitations that impact its applicability and generalizability. These shortcomings are evident in the studies reviewed, which often focus on controlled or large-scale industrial settings while overlooking broader contextual factors.

5.1. Limitations of existing literature

Most documented implementations occur in large-scale, urban manufacturing facilities in developed regions (e.g., Europe and North America), with limited exploration of smaller or rural production environments. This bias restricts the transferability of findings to diverse operational contexts, where infrastructure and resource availability may differ significantly [adapted from BEEAH, 2025; United Arab Emirates policies, 2024].

Few studies conduct thorough economic evaluations or life cycle assessments of AI-IIoT deployments, hindering understanding of long-term financial viability and environmental impacts. For instance, while performance metrics like accuracy rates are reported, the full ROI, including initial investments and maintenance costs, is rarely quantified, making it challenging to justify adoption in cost-sensitive manufacturing sectors [e.g., Aberger et al., 2025; Jakobs and Kroell, 2024].

AI models and IIoT sensors are highly sensitive to data freshness, calibration stability, and environmental variables (e.g., moisture, contamination, or sensor drift), leading to performance degradation in real-world conditions. Literature often highlights these issues but lacks detailed mitigation strategies, such as adaptive algorithms for heterogeneous production lines [e.g., Pučnik et al., 2024; Wang et al., 2024a-c].

While quantitative data from sensors dominates, qualitative aspects like operator training, cultural resistance, and human-AI interactions are underexplored. This imbalance limits holistic evaluations, as lean manufacturing's "people" principle (from Heinz et al.) requires addressing behavioral and organizational factors for successful integration [e.g., Fraccascia and Nastasi, 2023; Godinho Filho et al., 2024].

Many studies are based on short-term pilots or small datasets (e.g., limited annotated images), with few longitudinal assessments of sustained performance. This temporal limitation obscures insights into scalability and adaptability over time, particularly in dynamic manufacturing environments [e.g., Sirimewan et al., 2024; Cheng et al., 2024].

These limitations underscore the need for more rigorous, context-aware research to enhance the reliability of Digital Lean implementations.

5.2. Research gaps and future directions

Despite advancements in AI-IIoT applications for lean manufacturing, significant gaps remain in understanding their full potential for waste reduction, process efficiency, and operational performance. Addressing these gaps through targeted research can inform strategies for seamless integration, aligning with our study's mixed-methods evaluation.

There is a need for more case studies and comparative analyses in underrepresented contexts, such as small-scale or rural manufacturing facilities, to assess feasibility and performance. Future research could employ multi-site, mixed-methods designs to evaluate AI-IIoT synergies across varying production volumes and resource constraints, building on our single-case approach [e.g., expand from Zorpas, 2024; Martikkala et al., 2023].

Gaps exist in exploring how AI tools influence workforce dynamics, including training needs, trust in automated systems, and cultural shifts toward data-driven lean practices. Qualitative studies, such as extended interviews or ethnographic observations, could complement quantitative sensor data to develop frameworks for human-centric Digital Lean, addressing the "people" principle [e.g., Balińska et al., 2024; Toșa et al., 2024].

Research should prioritize cost-benefit analyses, life cycle assessments, and ROI modeling for AI-IIoT deployments, including sensitivity to factors like fleet sizes, data freshness, and seasonal disruptions. Longitudinal studies (e.g., over 5-10 years) could quantify sustained impacts on waste reduction and efficiency, informing policy and investment decisions [e.g., Naeem et al., 2024; Tumu et al., 2023].

Current models struggle with nonlinear relationships, dataset imbalances, and real-time adaptability in complex production lines. Future directions include developing hybrid AI frameworks (e.g., combining CNNs with Transformers) and standardized interoperability protocols for IIoT sensors, tested through simulations and pilots to enhance reliability [e.g., Grassel et al., 2025; Son and Ahn, 2025].

There is limited evidence on scaling AI-IIoT from pilots to enterprise-wide adoption, including challenges in data privacy and regulatory compliance. Interdisciplinary research involving engineers, policymakers, and managers could explore scalable strategies, such as modular implementation and predictive maintenance, to support broader Industry 4.0-lean integrations [e.g., Fang et al., 2023; EPA grants, 2022].

To mitigate these gaps, researchers should adopt collaborative, mixed-methods approaches like ours, combining quantitative IIoT metrics with qualitative stakeholder insights for triangulated findings. Partnerships with industry for real-world data access and funding for diverse settings could accelerate progress, ultimately advancing Digital Lean as a cornerstone of sustainable manufacturing. If needed, our study could serve as a foundation for such future investigations.

6. Suggested Mitigations and pathways forward

Based on the limitations and research gaps identified in previous studies, efforts were made to overcome these limitations and address the gaps.

Table3.3. Alignment of key findings with the research questions.

Research Question (Adapted)	Key Findings	Supporting Studies	Relevance to Our Study
RQ1: Which AI strategies have demonstrated the highest effectiveness across different stages of material management in manufacturing, and how have these been benchmarked or validated operationally?	AI strategies like convolutional neural networks (CNNs) and Transformers show high effectiveness in sorting and recycling stages, with CNNs achieving 78-98% accuracy in real-time operations and Transformers providing 99.75% stability under variable	Bonifazi et al. (2025); Wang et al. (2024a, b, c); Jurtsch et al. (2024); Fang et al. (2023); Martikkala et al. (2023)	These strategies validate IIoT-enabled lean practices in our study, where quantitative metrics (e.g., sorting accuracy from sensors) and qualitative validations (e.g., operator feedback) confirm effectiveness in waste reduction and efficiency, supporting the harmonious integration framework.

	conditions. Benchmarks include accuracy rates, recovery percentages (e.g., 98% for contaminants), and operational validations via lab-to-field tests, reducing inefficiencies by 30-45%. Predictive maintenance algorithms also excel in monitoring stages, minimizing downtime.		
RQ2: What technical, contextual, and data-related factors limit the transferability and large-scale deployment of AI-based systems, particularly in small-scale or resource-scarce manufacturing settings?	Technical factors include sensor drift, dataset imbalances, and computational demands; contextual issues involve infrastructure gaps and policy support in rural/small settings; data-related challenges encompass freshness, contamination, and imbalances, leading to performance drops (e.g., 20-40% in heterogeneous environments). These limit scalability, with most successes in large urban facilities.	Aberger et al. (2025); Jakobs and Kroell (2024); Pučnik et al. (2024); Cheng et al. (2024); Hassan et al. (2025); Sirimewan et al. (2024)	Our mixed-methods approach addresses these by evaluating IIoT deployments in a single case, highlighting limitations through qualitative insights (e.g., training needs) and quantitative data (e.g., performance degradation), informing strategies for broader transferability in lean manufacturing.
RQ3: How can AI integration in manufacturing be aligned with lean principles, life-cycle thinking, and policy instruments (e.g., extended producer responsibility)?	AI aligns with lean by enhancing muda reduction via real-time data (e.g., value stream mapping with sensors) and life-cycle thinking through predictive analytics for full product cycles. Policy instruments like extended producer responsibility encourage AI for sustainable sourcing and	Sanders et al. [36]; Meyer et al. (2018) [37]; Dombrowski and Richter [38]; Womack et al. (1990); Bitkom; Naeem et al. (2024); Tumu et al. (2023)	This alignment underpins our study's framework, where AI-IIoT integration is assessed for lean outcomes, using qualitative data on policy impacts and quantitative metrics on efficiency, reinforcing Industry 4.0-lean synergies for operational performance.

	recycling, reducing waste by 30% and supporting zero-defect production. Synergies create "Digital Lean" without conflicting with traditional tools.		
RQ4: What emerging applications of AI address underexplored material streams, such as construction or metal waste in manufacturing, and how do these extend the scope of sustainable lean frameworks?	Emerging AI applications include CNN classifiers for metal sorting (98.03% accuracy) and deep learning for construction materials (IoU 0.74-0.86 for aggregates), extending to textile and e-waste streams via behavior analysis and route optimization. These reduce costs, improve recovery, and address gaps in rural settings, broadening sustainable lean by incorporating predictive maintenance and circular flows.	Jurtsch et al. (2024); Farshadfar et al. (2025); Sirimewan et al. (2024); Hassan et al. (2025); Zorpas (2024)	Our study extends this by evaluating IIoT-AI in diverse streams, using mixed-methods to quantify waste reduction (e.g., via sensors) and qualitatively explore extensions to lean frameworks, enhancing the scope for comprehensive manufacturing sustainability

7. Summary of Key Findings and Responses to the Research Questions

This review synthesized and analyzed recent studies to evaluate how AI, integrated with Industrial Internet of Things (IIoT) sensors, contributes to Digital Lean implementation within manufacturing environments, enhancing waste reduction, process efficiency, and operational performance. Table 3 summarizes the main findings in relation to the four guiding research questions, highlighting demonstrated capabilities, persisting barriers, and emerging opportunities across the material management lifecycle in production processes.

8. Conclusion

AI is increasingly contributing to lean manufacturing by improving the accuracy and efficiency of material sorting, recovery, and system optimization within Industry 4.0 frameworks. Numerous studies have demonstrated the potential of AI-based approaches, including machine learning, computer vision, and IIoT sensor integration, in identifying and separating a wide range of materials such as plastics, metals, textiles, and electronic components in production lines.

These technologies not only enhance operational efficiency but also support the broader objectives of sustainability, resource conservation, and lean principles like muda elimination and zero-defect production, without conflicting with traditional tools.

Despite these advancements, several barriers continue to limit the large-scale implementation of AI-IIoT systems in real-world manufacturing contexts. Key challenges include the lack of standardized and diverse datasets, limited scalability of models trained in controlled environments, insufficient economic assessments, and gaps in regulatory support for digital transformations. Most AI solutions evaluated in academic research have not fully accounted for the variability and unpredictability of industrial material streams, which often involve complex components, contamination, and heterogeneous production conditions.

To fully realize AI's transformative potential in manufacturing, future research must adopt a more integrated and practical approach. This includes conducting comprehensive cost-benefit analyses, establishing shared data standards, developing robust models for diverse and difficult material types, particularly plastics and metals, and ensuring alignment with lean principles and policy instruments like extended producer responsibility. Adaptive AI systems capable of learning in real-time and functioning under variable conditions should also be prioritized. In the near future, emphasis should be placed on pilot studies that test AI-IIoT-based sorting, monitoring, and predictive maintenance systems on real-world heterogeneous production streams across both large-scale and smaller facilities to assess scalability and data reliability. Over the following stages, stronger collaboration between researchers, policymakers, and industry is needed to develop economic evaluation models with supportive policy incentives, and investment mechanisms should be developed to facilitate industrial adoption and ensure equitable implementation. In the long term, combining AI with complementary IIoT technologies and lean methodologies can drive sustainable manufacturing excellence, as explored in our mixed-methods study through quantitative sensor data and qualitative insights. This integration positions Digital Lean as a cornerstone for achieving operational performance gains while addressing global sustainability goals.

9. Recommendations

- Adopt standardized implementation strategies using industrial IoT sensors in key production areas (such as sorting lines) to mitigate risks.
- Invest in workforce training and data protection to implement robust data security measures to alleviate privacy concerns, enhance trust, and enable real-time decision-making without disrupting traditional workflows.
- Conduct ongoing ROI assessments, including initial investments in sensors and AI algorithms.
- Conduct multiple case studies or longitudinal research in underrepresented environments (such as small or rural facilities) to evaluate the scalability and applicability of digital Lean frameworks, addressing gaps related to geographic bias and limited sample size.

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