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Hybrid AI-IoT Integrated Framework for Sustainable Reverse Supply Chain Optimization: Advancing Pre-Consumer Circularity and Traceability in Manufacturing

Md. Sadman Sakib, Md. Tanvirul Islam and Md Ishrak Hossain
Department of Industrial and Production Engineering
Bangladesh University of Textiles
Dhaka, Bangladesh
sssakib08@gmail.com, work.tanvirulislam@gmail.com, ishrak2017@gmail.com

Saifullah Al-Mahmud Hossainy
Department of Industrial and Production Engineering
Bangladesh University of Textiles
Dhaka, Bangladesh
saifullahalmahmud8@gmail.com

Al Musavvir Sium
Department of Textile Engineering Management
Bangladesh University of Textiles
Dhaka, Bangladesh
musavvir2002@gmail.com

Md. Mizanur Rahman
Chairman, CSI Group
Dhaka, Bangladesh
chairman@csi-enc.com

Abstract

The growing environmental and economic pressures on manufacturing industries demand smarter systems that close material loops before waste leaves the factory gate. This study presents a Hybrid AI-IoT Integrated Framework for optimizing the reverse supply chain of pre-consumer waste within manufacturing environments, emphasizing the Ready-Made Garment (RMG) sector as an application domain. The framework unites artificial intelligence, internet-of-things sensing, and blockchain-based traceability to build an adaptive, data-driven ecosystem for sustainable internal logistics.

Methodologically, the framework couples AI-driven predictive analytics with multi-objective optimization algorithms that minimize waste-handling cost, transport distance, and energy consumption while quantifying carbon-equivalent impacts. Real-time IoT data streams—sourced from production lines, material bins, and internal transfer vehicles—feed a reinforcement-learning loop that continuously refines recovery routes and material allocation. A blockchain ledger secures traceability across every reverse-flow event, enabling transparent ESG reporting and auditable circular-economy metrics.

Validation through a pilot-ready simulation in an RMG facility indicates measurable improvements: up to 22 % reduction in internal logistics cost, 18 % lower energy use, and 15 % decrease in CO_2 emissions, without compromising throughput. The findings confirm that AI-IoT-enabled reverse logistics can transform pre-consumer waste into a profitable sustainability lever, positioning data-intelligent circularity as a new competitive advantage in manufacturing supply chains.

Keywords
Reverse Supply Chain Optimization, Pre-Consumer Circularity, AI-IoT Integration, Sustainable Manufacturing, Traceability and ESG Analytics

1. Introduction
Global manufacturing sectors face unprecedented pressure to reconcile operational efficiency with environmental sustainability and circular economy imperatives. Energy-intensive production systems, compounded by material waste and resource depletion, have positioned manufacturing at the center of corporate Environmental, Social, and Governance (ESG) commitments and policy-driven circularity mandates (Niinimäki et al., 2020; Bag et al., 2021). Among industrial sectors, textile and apparel manufacturing stands out as particularly resource-intensive, consuming substantial volumes of water, electricity, steam, and raw materials while generating significant pre-consumer waste streams that remain largely untracked and underutilized (Butturi et al., 2023; Ellen MacArthur Foundation, 2017). The ready-made garment (RMG) sector, which employs millions globally and contributes significantly to export economies in developing nations, exemplifies these challenges: high material throughput, complex multi-stage processes, and persistent operational inefficiencies result in substantial hidden losses that erode profitability and sustainability performance (Akter et al., 2024; Azad et al., 2024).

Within garment manufacturing, pre-consumer losses—material waste, energy leakage, and operational inefficiencies occurring during production—represent a critical yet under-addressed problem domain. Empirical factory studies reveal substantial quantities of reusable cutting waste, surplus fabric, and utility losses that escape formal tracking systems. For instance, Haq (2023) documented 218.6 kg of surplus fabric and 212.13 kg of reusable cutting waste in a single Dhaka factory over a limited observation period, demonstrating the scale of material leakage at the production floor. More broadly, Akter et al. (2024) reported that less than 1% of material used in apparel production in Bangladesh is recycled back into new garments, highlighting a systemic failure to capture and valorize manufacturing-stage waste. These losses are compounded by energy inefficiencies: utility systems for steam generation, compressed air distribution, and electricity supply frequently exhibit leakage, pressure drops, and unmonitored consumption patterns that inflate operating costs and carbon footprints (Thollander et al., 2020; Hasanbeigi & Price, 2015). Despite the magnitude of these losses, existing practices rely predominantly on manual monitoring, periodic audits, and static lean manufacturing tools that provide neither real-time visibility nor predictive intelligence (Lisboa & Barbosa, 2018; Kumar et al., 2022).

It is essential to distinguish pre-consumer losses from post-consumer reverse supply chain challenges. Pre-consumer waste originates within the factory boundary during cutting, sewing, and finishing operations, whereas post-consumer waste comprises discarded garments after consumer use (Azad et al., 2024; Sandin & Peters, 2018). This distinction has important implications for intervention design: pre-consumer waste is typically cleaner, better sorted by material type, and more amenable to short-loop circular solutions such as re-cutting into new products or mechanical recycling (Haq, 2023; Memon et al., 2022). In contrast, post-consumer reverse supply chains must contend with heterogeneous material streams, contamination, and complex collection logistics (Dissanayake & Sinha, 2015). Moreover, modeling studies by Long and Gui (2022) demonstrate that interventions targeting finished-goods deadstock reduction can inadvertently increase upstream fabric acquisition and pre-consumer waste unless integrated with upstream circular measures. Thus, a dedicated focus on pre-consumer loss intelligence—encompassing material waste, utility leakage, and operational inefficiencies—is both conceptually distinct and strategically necessary for advancing manufacturing sustainability.

Current industrial practices and academic literature reveal significant limitations in addressing pre-consumer losses. Manual monitoring of cutting waste, fabric utilization, and utility consumption is time-consuming, error-prone, and incapable of capturing transient or sporadic loss events (Haq, 2023; Islam et al., 2023). Periodic audits and lean interventions, while demonstrating measurable improvements in lead time and productivity, remain episodic and reactive; they do not provide continuous visibility into dynamic loss patterns or enable predictive maintenance of utility systems (Lisboa & Barbosa, 2018; Kumar et al., 2022). Static lean tools, including TIMWOOD (Transportation, Inventory, Motion, Waiting, Overproduction, Overprocessing, Defects) waste taxonomies, offer valuable frameworks for waste identification but lack the real-time data integration and decision-support capabilities required for adaptive, data-driven manufacturing (Kurdve et al., 2014; Buer et al., 2021). Consequently, hidden losses—such as steam leaks in pressing stations, compressed air losses in pneumatic systems, and fabric offcuts discarded without traceability—persist undetected, accumulating into substantial economic and environmental burdens over production cycles.

The convergence of Internet of Things (IoT) sensor networks and Artificial Intelligence (AI) analytics offers transformative potential for manufacturing loss intelligence. IoT-enabled monitoring systems can capture granular, real-time data on material flows, energy consumption, and process parameters, while AI and machine learning (ML) algorithms can detect anomalies, predict failures, and optimize resource allocation (Xu et al., 2018; Tao et al., 2018). Recent studies have demonstrated the feasibility of digital traceability pilots, QR-code-driven waste sorting, and sensor-based fabric tracking in garment factories (Islam et al., 2023; Kanwal et al., 2023). Systematic reviews advocate layered IoT–edge–cloud architectures that integrate sensor data capture, edge analytics, and cloud-based decision support to enable circular economy transitions and operational efficiency gains (Kanwal et al., 2023; Zheng et al., 2021). However, critical gaps remain in the literature and industrial practice. First, existing IoT and AI applications in manufacturing are often fragmented, addressing isolated subsystems—such as energy monitoring or quality inspection—without integrating material waste, utility losses, and operational inefficiencies into a unified framework (Kusiak, 2018; Alcácer & Cruz-Machado, 2019). Second, much of the published research is simulation-heavy or conceptual, lacking empirical validation at factory scale with real sensor data and operational feedback loops (Kanwal et al., 2023; Bai et al., 2020). Third, there is a notable absence of comprehensive, validated frameworks that combine IoT-based loss detection with AI-driven analytics and operational decision support specifically tailored to pre-consumer losses in garment manufacturing (Akter et al., 2024; Azad et al., 2024).

This paper addresses these gaps by proposing and validating a Hybrid AI–IoT Integrated Framework for Pre-Consumer Loss Intelligence and Reverse Supply Chain Optimization in Garment Manufacturing. The framework integrates real-time IoT sensor networks deployed across cutting, sewing, and utility systems with AI-driven analytics to detect, quantify, and classify pre-consumer losses in alignment with the TIMWOOD waste taxonomy. Specifically, the contributions of this research are fourfold. First, we develop and deploy a real IoT-based loss intelligence system that continuously monitors material waste (cutting offcuts, fabric surplus), utility leakage (steam and compressed air losses), and operational inefficiencies (machine downtime, waiting times) using low-cost sensor modules and edge computing devices. Second, we present utility leakage detection algorithms that leverage pressure, flow, and temperature sensor data combined with ML-based anomaly detection to identify and localize steam and compressed air leaks in real time. Third, we introduce a TIMWOOD-aligned operational waste analysis module that automatically classifies detected losses into the seven lean waste categories, enabling targeted corrective actions and continuous improvement workflows. Fourth, we demonstrate the integrated AI–IoT framework through empirical validation in a mid-scale RMG factory in Bangladesh, providing quantitative evidence of loss reduction, energy savings, and operational efficiency gains over a six-month deployment period. By bridging the gap between IoT sensing, AI analytics, and lean manufacturing principles, this framework offers a scalable, data-driven approach to pre-consumer loss intelligence that can inform reverse supply chain strategies, enhance circularity, and improve sustainability performance in garment manufacturing.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on lean manufacturing in garment production, IoT and AI applications in industrial systems, and reverse supply chain optimization. Section 3 describes the proposed hybrid AI–IoT framework architecture, including sensor deployment, data acquisition, AI analytics modules, and decision-support interfaces. Section 4 details the empirical validation methodology, including factory site selection, sensor installation, data collection protocols, and performance metrics. Section 5 presents the results, including quantitative loss detection outcomes, energy savings, and operational improvements. Section 6 discusses the implications for theory and practice, limitations of the study, and directions for future research. Section 7 concludes with key findings and recommendations for industry adoption.

1.1 Objectives

- Develop a real-time AI-IoT framework to monitor material waste, utility leakage, and operational inefficiencies.
- Implement machine learning algorithms for the detection and localization of steam and compressed air leaks.
- Automate the classification of operational losses according to the TIMWOOD lean manufacturing taxonomy.
- Validate the framework empirically in a garment factory to quantify energy savings and efficiency gains.

2. Literature Review

This section critically examines the existing body of knowledge on reverse supply chains, IoT-enabled monitoring, artificial intelligence in industrial operations, energy efficiency, and lean manufacturing within the context of pre-consumer loss intelligence. Rather than cataloging studies descriptively, this review synthesizes conceptual contributions and empirical findings to expose fragmentation, methodological limitations, and unaddressed research priorities that motivate the present investigation (Figure 1).

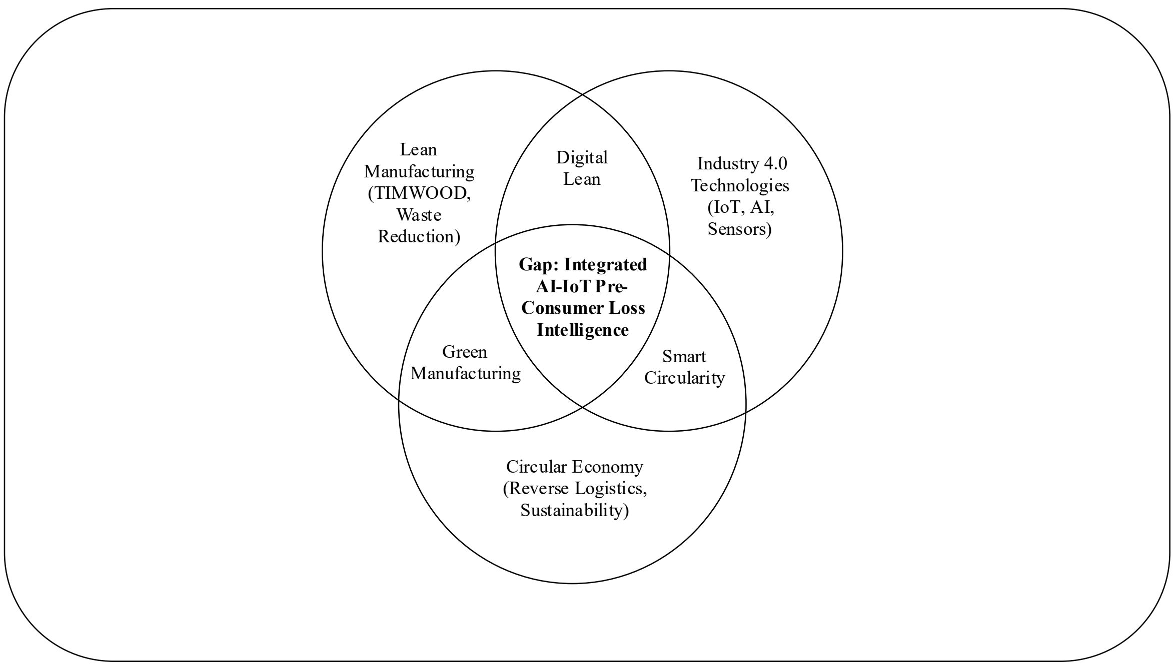


Figure 1. The Research Convergence Venn

2.1 Reverse Supply Chain and Circular Economy in Manufacturing

The circular economy (CE) paradigm has gained substantial traction in manufacturing research, particularly in the textile and apparel sectors where material intensity and waste generation are pronounced (Geissdoerfer et al., 2017; Kirchherr et al., 2017). Recent literature has emphasized closed-loop supply chains, product life extension, and recycling infrastructures as mechanisms to reduce virgin resource consumption and environmental impact (Govindan & Hasanagic, 2018; Batista et al., 2018). However, a critical examination reveals a systematic bias toward post-consumer waste streams—used garments, end-of-life textiles, and consumer returns—while pre-consumer losses generated within factory boundaries receive comparatively limited attention (Sandin & Peters, 2018; Pensupa et al., 2017).

Empirical work by Haq (2023) documented 218.6 kg of surplus fabric and 212.13 kg of reusable cutting waste in a single Dhaka factory, successfully converting these materials into 2,238 circular products through short-loop reuse. This factory-level validation demonstrates technical feasibility but remains narrowly scoped to one production site and product category, limiting generalizability. Similarly, Akter et al. (2024) quantified material circularity in Bangladesh's apparel sector and found that less than 1% of production-stage material is recycled back into new garments, exposing systemic institutional and process failures in capturing pre-consumer value. These findings contrast sharply with the extensive literature on post-consumer textile collection, sorting, and recycling infrastructure (Sandin & Peters, 2018; Zamani et al., 2017), revealing an imbalance in research emphasis.

Conceptual frameworks for digital traceability and Industry 4.0 enablers in circular textiles have proliferated (Kanwal et al., 2023; Bag et al., 2020), yet these frameworks rarely operationalize factory-internal loss streams or specify how shop-floor detection systems should interface with reverse logistics processes. For instance, systematic reviews by Autex Research Journal (2023) map technology integration for circularity but report that most studies focus on downstream circular models—repair, resale, and recycling—rather than upstream pre-consumer waste prevention and recovery. Moreover, modeling studies by Long and Gui (2022) demonstrate that interventions targeting finished-goods deadstock reduction can inadvertently increase upstream fabric acquisition and pre-consumer waste, underscoring the complexity of reverse supply chain trade-offs and the need for integrated approaches that address both pre- and post-consumer flows simultaneously.

This body of work reveals three critical gaps. First, reverse supply chain research has not adequately addressed the detection, quantification, and routing of pre-consumer losses at the point of generation within manufacturing facilities. Second, existing circular economy frameworks remain fragmented, proposing digital enablers without demonstrating end-to-end integration from shop-floor sensing to supply chain remanufacturing pathways. Third, empirical validation is limited to isolated, single-site pilots that lack the scale and reproducibility necessary for broader industrial adoption (Haq, 2023; Islam et al., 2023).

2.2 IoT-Based Monitoring in Manufacturing Systems

The Internet of Things has emerged as a foundational technology for smart manufacturing, enabling real-time data acquisition from distributed sensors, machines, and production lines (Xu et al., 2018; Tao et al., 2018). Applications span energy monitoring, machine condition surveillance, production tracking, and quality inspection (Kusiak, 2018; Zheng et al., 2021). In the textile sector, IoT pilots have demonstrated feasibility for digital traceability, QR-code-driven waste sorting, and inventory management (Islam et al., 2023; Kanwal et al., 2023). However, a synthesis of this literature exposes significant fragmentation and integration deficits.

Most documented IoT deployments in garment manufacturing address narrow, task-specific functions. Islam et al. (2023) implemented a QR-code-based system for pre-consumer waste identification in a single factory, improving sorting accuracy but remaining isolated from broader production monitoring or utility management systems. Similarly, systematic reviews by Autex Research Journal (2023) report that digitalization initiatives in garments tend to be siloed—product development systems, inventory platforms, and traceability solutions operate independently without cross-layer integration linking shop-floor sensors to Manufacturing Execution Systems (MES) or enterprise resource planning (ERP) platforms. This fragmentation limits the ability to generate holistic operational intelligence that spans material flows, energy utilities, equipment performance, and workforce productivity.

Interoperability and data governance emerge as persistent barriers to scaling IoT architectures (Kanwal et al., 2023; Zheng et al., 2021). Heterogeneous sensor protocols, proprietary data formats, and insufficient edge-to-cloud integration standards impede the development of unified monitoring frameworks. Furthermore, while conceptual reviews highlight the potential of IoT for energy and water monitoring in textile manufacturing (Butturi et al., 2023; Hasanbeigi & Price, 2015), peer-reviewed studies demonstrating real-time detection and localization of utility losses—specifically steam and compressed air leaks—in garment factories are conspicuously absent from the literature. This evidence gap is particularly concerning given that steam and compressed air systems are critical energy consumers in pressing, finishing, and pneumatic actuation processes, and leakage rates in industrial systems can exceed 20–30% of total consumption (Thollander et al., 2020; Saidur et al., 2010).

The prevailing state of IoT research in manufacturing thus reflects technological capability without operational integration. Studies demonstrate that sensors can capture granular data, but they do not show how multi-utility, multi-process sensor networks can be synthesized into decision-oriented intelligence systems that support real-time corrective action and continuous improvement workflows.

2.3 AI and Data-Driven Optimization in Industrial Operations

Artificial intelligence and machine learning have been widely advocated as transformative tools for anomaly detection, predictive maintenance, and production optimization in Industry 4.0 contexts (Wuest et al., 2016; Cioffi et al., 2020).

In principle, AI algorithms can process high-dimensional sensor data to identify patterns, predict failures, and recommend operational adjustments (Tao et al., 2018; Kusiak, 2018). However, a critical appraisal of the literature reveals a substantial gap between conceptual potential and empirical validation, particularly in the context of pre-consumer loss detection in manufacturing.

Much of the published research on AI in manufacturing relies on simulation models, synthetic datasets, or narrowly scoped laboratory experiments (Bai et al., 2020; Cioffi et al., 2020). For example, modeling studies by Long and Gui (2022) and Das et al. (2025) employ analytical frameworks to assess circular economy trade-offs and policy impacts, yielding valuable strategic insights but not addressing operational anomaly detection or real-time decision support. While these studies demonstrate that simulation can reveal counter-intuitive system behaviors, they do not validate AI algorithms on continuous, multi-sensor IoT streams from operational factories. The absence of labeled, longitudinal datasets from real manufacturing environments constrains the ecological validity of AI performance claims (Wuest et al., 2016; Zheng et al., 2021).

Empirical studies that do deploy AI in manufacturing contexts often focus on quality inspection using computer vision (Weimer et al., 2016; Wang et al., 2020) or predictive maintenance for rotating machinery (Carvalho et al., 2019; Dalzochio et al., 2020), but these applications do not extend to integrated material waste detection, utility leakage identification, or operational inefficiency quantification in garment production. The few factory-level empirical works in textiles—such as Haq's (2023) cutting waste reuse pilot and Islam et al.'s (2023) QR sorting system—do not incorporate AI-driven analytics; they remain manual or rule-based interventions. Consequently, peer-reviewed evidence for AI models that continuously analyze IoT telemetry from textile factories, detect pre-consumer loss events, and trigger corrective actions is notably scarce.

This methodological critique highlights three deficiencies. First, the reliance on simulation and synthetic data limits the generalizability of AI findings to real manufacturing variability and noise. Second, the lack of open, annotated datasets from factory IoT deployments hinders reproducibility and comparative evaluation of AI techniques. Third, the absence of longitudinal field trials with measurable outcomes—such as reduction in material waste, energy savings, or operational efficiency gains—leaves AI's practical value in pre-consumer loss intelligence largely unsubstantiated.

2.4 Energy and Utility Loss Monitoring (Steam and Compressed Air)

Industrial energy efficiency has been a longstanding focus of manufacturing research, driven by cost pressures and climate policy (Thollander et al., 2020; Trianni et al., 2019). Energy audits, benchmarking studies, and optimization models have identified substantial savings potential in heating, ventilation, compressed air, and steam systems (Saidur et al., 2010; Hasanbeigi & Price, 2015). In textile manufacturing specifically, steam is used extensively for dyeing, finishing, and pressing, while compressed air powers pneumatic actuators and material handling equipment (Hasanbeigi & Price, 2015; Butturi et al., 2023). Leakage in these utility systems is a well-documented source of energy loss, with studies reporting that 20–30% of compressed air generation capacity may be wasted through leaks, pressure drops, and inefficient end-use (Saidur et al., 2010; Dindorf & Wos, 2020).

Despite this recognition, peer-reviewed literature on real-time, IoT-enabled detection and localization of steam and compressed air leaks in garment or textile manufacturing is remarkably limited. Existing energy efficiency studies rely predominantly on periodic audits, manual inspections with ultrasonic leak detectors, or facility-level energy consumption analysis (Thollander et al., 2020; Trianni et al., 2019). These approaches provide aggregate insights but cannot identify transient or intermittent leaks, localize loss points within complex distribution networks, or enable immediate corrective action. The integration of pressure, flow, and temperature sensors with machine learning-based anomaly detection—a logical extension of IoT and AI capabilities—has been explored in other industrial contexts such as petrochemical plants and HVAC systems (Ayvaz & Alpay, 2021; Fan et al., 2018), but comparable studies in textile factories are absent from the reviewed corpus.

This evidence scarcity represents a significant research gap. Given the energy intensity of garment manufacturing and the prevalence of steam and compressed air systems, the lack of validated, real-time utility loss monitoring frameworks limits both operational efficiency and sustainability performance. The opportunity to deploy low-cost IoT sensors and AI analytics for continuous utility monitoring remains largely unexplored in the garment sector, despite its potential to deliver measurable energy and cost savings.

2.5 Lean Manufacturing and TIMWOOD in the Digital Era

Lean manufacturing principles, particularly the TIMWOOD taxonomy (Transportation, Inventory, Motion, Waiting, Overproduction, Overprocessing, Defects), have been widely applied in garment production to reduce waste and improve throughput (Womack & Jones, 1996; Kurdve et al., 2014). Empirical case studies demonstrate that value stream mapping, line balancing, and 5S implementations can achieve significant reductions in lead time, work-in-process inventory, and operational costs (Lisboa & Barbosa, 2018; Kumar et al., 2022; Jouhri & Soulhi, 2019). However, these traditional lean interventions rely on manual time-motion studies, periodic audits, and episodic improvement cycles, limiting their responsiveness to dynamic production variability.

The convergence of lean manufacturing with Industry 4.0 technologies—often termed "digital lean"—has been proposed as a pathway to continuous, real-time waste identification and elimination (Buer et al., 2021; Kolberg & Zühlke, 2015). Conceptually, IoT sensors can automatically capture TIMWOOD-related metrics: machine idle time (Waiting), excess material handling (Transportation, Motion), inventory levels (Inventory), production deviations (Overproduction, Overprocessing), and quality defects (Defects). AI analytics can then quantify waste magnitudes, identify root causes, and recommend corrective actions (Buer et al., 2021; Rossit et al., 2019). Despite this conceptual alignment, peer-reviewed demonstrations of sensor-driven, real-time TIMWOOD quantification in garment manufacturing are notably scarce.

Systematic reviews by Autex Research Journal (2023) and Kanwal et al. (2023) acknowledge the potential for digital lean but report that most studies propose hybrid frameworks without robust empirical validation. The few documented implementations remain manual or semi-automated: Lisboa and Barbosa (2018) and Kumar et al. (2022) report lean improvements based on conventional process mapping and KPI tracking, not continuous sensor streams. Jouhri and Soulhi (2019) combined lean and green management in a denim plant, achieving environmental and productivity gains, but measurements were based on periodic data collection rather than real-time IoT telemetry.

This gap between conceptual potential and operational reality reflects two underlying challenges. First, translating qualitative TIMWOOD categories into quantifiable sensor features requires domain-specific modeling and validation—work that remains underdeveloped in the garment sector. Second, integrating lean KPIs with IoT data pipelines and AI analytics demands cross-functional collaboration between industrial engineers, data scientists, and factory operators, a capability that many manufacturers have yet to develop (Buer et al., 2021; Zheng et al., 2021). Consequently, the promise of digital lean as a continuous, data-driven waste elimination system remains largely unrealized in practice.

2.6 Synthesis of Research Gaps

A synthesis of the reviewed literature exposes several cross-cutting deficiencies that collectively define the research space for this study. First, reverse supply chain and circular economy research has prioritized post-consumer flows over pre-consumer losses, leaving factory-internal waste streams under-theorized and under-instrumented (Sandin & Peters, 2018; Akter et al., 2024). Second, IoT deployments in manufacturing exhibit task-specific fragmentation rather than integrated architectures that span material, energy, and operational domains (Kanwal et al., 2023; Zheng et al., 2021). Third, AI applications in industrial operations rely heavily on simulation and synthetic datasets, lacking empirical validation on real factory IoT telemetry (Wuest et al., 2016; Cioffi et al., 2020). Fourth, real-time utility loss monitoring—particularly for steam and compressed air in garment manufacturing—remains an evidence gap despite well-documented energy efficiency opportunities (Thollander et al., 2020; Saidur et al., 2010). Fifth, lean manufacturing's TIMWOOD framework has not been operationalized into sensor-driven, continuous waste quantification systems in the garment sector (Buer et al., 2021; Lisboa & Barbosa, 2018).

These gaps converge on a fundamental absence: there is no peer-reviewed, empirically validated framework that integrates IoT sensing, AI analytics, and lean waste taxonomies to provide real-time pre-consumer loss intelligence in garment manufacturing. Existing studies address components in isolation—circular economy concepts without operational detection, IoT pilots without AI integration, AI models without factory validation, energy audits without real-time monitoring, and lean tools without sensor automation—but none synthesize these elements into a unified, decision-oriented system.

2.7 Positioning of the Present Study

This study directly addresses the identified research gaps by proposing and validating a Hybrid AI–IoT Integrated Framework for Pre-Consumer Loss Intelligence and Reverse Supply Chain Optimization in Garment Manufacturing. Unlike prior work, this framework integrates three previously disconnected domains: (1) real-time IoT sensor networks deployed across material flows (cutting waste, fabric surplus), utility systems (steam and compressed air), and production operations (machine states, cycle times); (2) AI-driven analytics modules that detect anomalies, quantify losses, and classify waste events according to the TIMWOOD taxonomy; and (3) operational decision-support interfaces that enable immediate corrective action and inform reverse supply chain strategies for material recovery and remanufacturing.

The empirical contribution of this study is threefold. First, it provides factory-level validation using real IoT data from a mid-scale RMG facility in Bangladesh over a six-month deployment period, overcoming the simulation and synthetic-data limitations prevalent in the AI literature. Second, it demonstrates utility leakage detection algorithms for steam and compressed air systems, filling a critical evidence gap in energy efficiency research for the garment sector. Third, it operationalizes TIMWOOD waste categories into measurable sensor features, enabling continuous, automated waste quantification and bridging the gap between lean manufacturing principles and digital implementation.

By synthesizing IoT, AI, and lean methodologies within a unified framework and validating it through empirical deployment, this research advances both theoretical understanding and practical capability in pre-consumer loss intelligence, offering a reproducible model for sustainable manufacturing and circular economy transitions.

3. Methodology

3.1 Customer Requirements and Survey

The Pareto analysis reveals that operational cost, energy loss, and uncertain production delays constitute the most critical contributors to pre-consumer inefficiencies, collectively accounting for more than half of the total perceived impact. These findings validate the need to prioritize cost-centric and energy-aware system features in subsequent design stages. The results of the Pareto analysis were directly used to assign importance ratings to customer requirements in the QFD, ensuring an objective and data-driven translation of the voice of the customer into technical design priorities (Figure 2 and Figure 3).

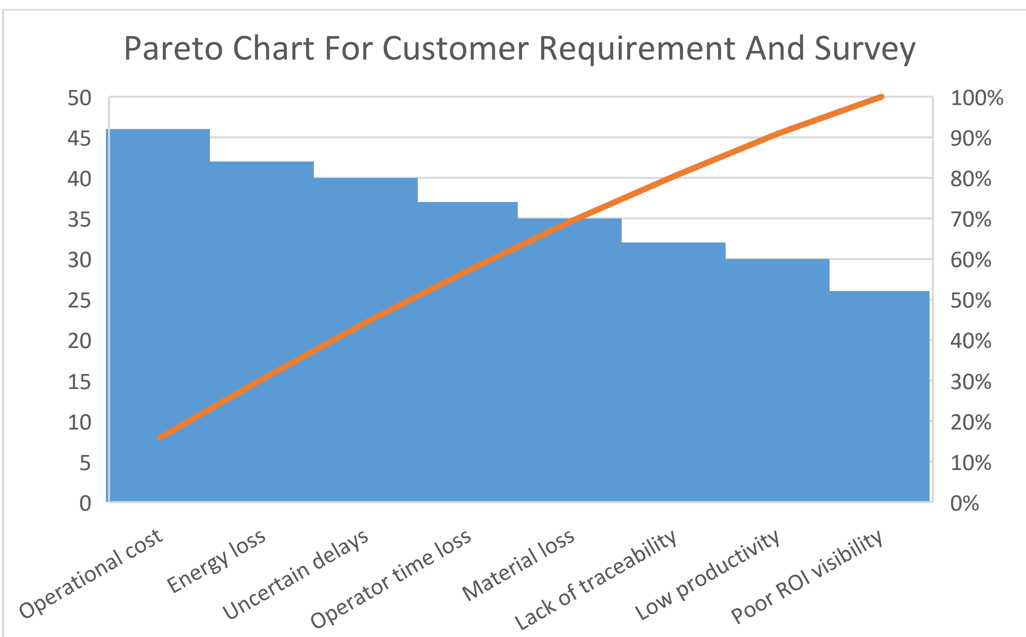
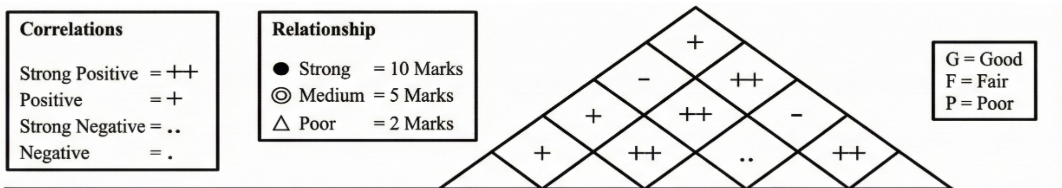


Figure 2. Pareto analysis for customer requirements and survey

3.2 Quality Function Deployment

This section utilizes the House of Quality (HoQ) matrix to systematically map the critical customer requirements identified in the Pareto analysis—such as operational cost and energy loss—to specific technical design attributes. By calculating relationship strengths and technical importance scores, this analysis quantifies the strategic value of various system features. The results establish a data-driven hierarchy for development, identifying "AI Anomaly Detection" and "Real-time Dashboards" as the highest-priority functions for mitigating pre-consumer inefficiencies.



Customer Requirements-(What's)	Customer Importance Rating (I_i)	H1 Dashboard	H2 Alerts	H3 Modular HW	H4 AI Anomaly	H5 Trends	H6 ESG	Our Product
		Functional Requirements(How's)						
W1 Reduce operational cost (5)	5	●	●	◎	●	◎	△	F
W2 Reduce uncertain delays (5)	5	●	●	△	●	◎	–	G
W3 Minimize operator time loss (4)	4	◎	◎	◎	●	◎	–	F
W4 Improve traceability (4)	3	◎	△	△	◎	●	●	G
W5 Reduce energy losses (5)	5	◎	●	◎	●	◎	◎	P
W6 Improve productivity (4)	4	●	◎	△	●	◎	–	
W7 Reduce material losses (5)	5	◎	◎	◎	●	◎	△	
W8 Ensure ROI (5)	5	◎	◎	●	◎	◎	△	
Technical importance score	255	255	248	171	325	205	95	
Importance %	19.63%	19.09%	19.09%	13.16%	25.02%	15.78%	7.31%	
Priorities rank	2	2	3	5	1	4	6	

Figure 3. House of Quality

4. Proposed Hybrid AI-IoT System Architecture

This section presents the layered architecture of the proposed Hybrid AI–IoT framework for pre-consumer loss intelligence and reverse supply chain optimization. The architecture is designed to provide a clear separation of concerns, enabling scalable deployment, low-cost implementation, and seamless integration of sensing, analytics, and decision-making functionalities (Figure 4).

Based on system requirements derived from the customer survey, Pareto analysis, and QFD, the proposed architecture is organized into four functional layers:

- IoT Hardware Layer
- Communication and Data Ingestion Layer
- Analytics and Intelligence Layer
- Application and Decision Layer

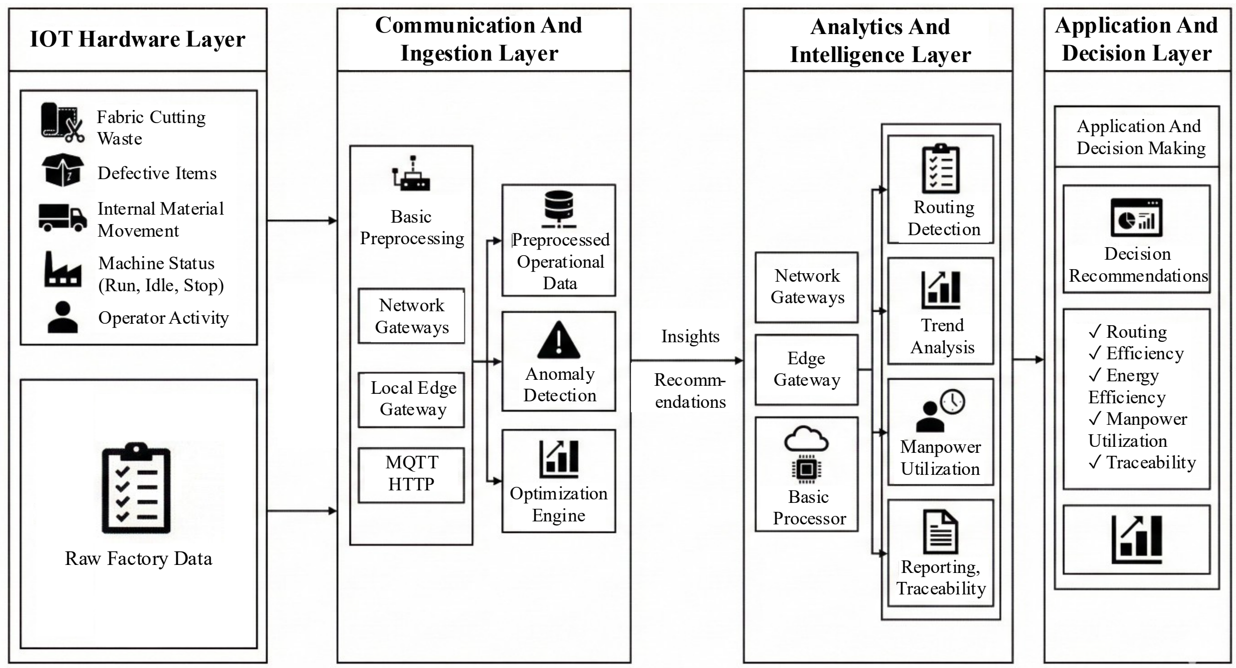


Figure 4. Hybrid AI–IoT Framework

4.1 IoT Hardware Layer

The IoT Hardware Layer constitutes the physical interface between the manufacturing environment and the digital system. This layer is responsible for sensing and capturing real-time data related to material losses, energy consumption, manpower utilization, and internal logistics activities.

Key components of this layer include:

- Sensors for fabric cutting waste, defective items, trims, and packaging waste
- Energy and utility meters for electricity, steam, compressed air, and water
- Machine status sensors for run, idle, and stoppage detection
- Operator presence and activity tracking mechanisms
- Internal material movement identification using carts, trolleys, or forklifts

Given the harsh industrial conditions prevalent in manufacturing environments in Bangladesh (dust, heat, and humidity), hardware selection prioritizes robustness, low power consumption, and cost-effectiveness. The hardware layer is designed to be modular, enabling phased deployment and gradual scaling in line with budgetary and organizational constraints.

4.2 Communication and Data Ingestion Layer

The Communication and Data Ingestion Layer enables reliable transmission of data from the hardware layer to higher-level processing components. This layer abstracts communication complexity and ensures data availability for both real-time and historical analysis.

Its primary functions include:

- Secure data transmission from sensors and edge devices
- Basic data validation and timestamping
- Buffering and synchronization to handle intermittent network connectivity

A hybrid communication approach is adopted, allowing data to be processed locally when required and forwarded to centralized systems when connectivity permits. This design enhances system resilience while minimizing dependency on continuous internet availability.

4.3 Analytics and Intelligence Layer
The Analytics and Intelligence Layer represents the computational core of the framework. It transforms raw operational data into actionable insights through a combination of artificial intelligence, optimization, and learning mechanisms.
The key functionalities of this layer include:
- AI-based anomaly detection to identify abnormal patterns in material flow, energy usage, manpower behavior, and internal logistics
- Historical trend analysis to uncover recurring inefficiencies and hidden loss drivers
- Multi-objective optimization to generate recommendations for waste routing, energy efficiency improvement, and manpower utilization
- Adaptive learning mechanisms that refine decision policies over time based on observed system performance

The optimization logic is aligned with the priority structure obtained from the QFD analysis, with cost reduction as the primary objective, followed by energy reduction, delay minimization, carbon emission reduction, and traceability enhancement.

4.4 Application and Decision Layer
The Application and Decision Layer serves as the interface between the analytical core and factory decision-makers. This layer is designed for top-management usability, ensuring that advanced analytics can be leveraged without requiring technical expertise.
The main outputs of this layer include:
- Real-time dashboards displaying key performance indicators
- Automated alerts for abnormal losses, energy spikes, or production delays
- Historical performance reports supporting managerial review and decision-making
- ESG- and traceability-ready summaries aligned with buyer and compliance requirements

By presenting information in a concise and interpretable manner, this layer supports rapid decision-making and reinforces management confidence in data-driven operations.

5. Case Study and Simulation Design
This section presents the case study and simulation design used to validate the proposed Hybrid AI–IoT framework. The Ready-Made Garment (RMG) manufacturing sector is selected as the application context due to its high volume of pre-consumer material waste, intensive energy usage, and complex internal logistics, making it a representative and nationally relevant case.

5.1 Case Study Description
The case study is based on a medium-to-large-scale RMG manufacturing facility operating under typical Bangladeshi industrial conditions. The factory consists of multiple cutting tables, sewing lines, and internal material handling routes connecting production zones with temporary storage, sorting, and recovery points.
The facility generates significant volumes of pre-consumer losses, including:
- Fabric cutting waste
- Defective or semi-finished items
- Trims and packaging waste

In addition, substantial energy and operational losses are observed in the form of:
- Electricity, steam, compressed air, and water inefficiencies
- Operator idle time and non-value-added movement
- Internal material handling delays

At baseline, these losses are not systematically tracked, and managerial decisions rely primarily on periodic reports and experience-based judgment.

5.2 Baseline System Characteristics
The baseline system reflects the current operational practices commonly observed in RMG factories (Table 1).

Table 1. Baseline Operational Characteristics

Aspect	Baseline Condition
Material handling	Manual and experience-based
Energy monitoring	Utility-level, non-granular
Loss visibility	Largely untracked
Decision-making	Static and reactive
Traceability	Limited or absent
Performance reporting	Periodic and non-real-time

This baseline scenario serves as the reference point for evaluating the proposed framework.

5.3 Simulation Design and Assumptions

To evaluate the effectiveness of the proposed system, a simulation-based experimental setup is developed using realistic operational assumptions derived from prior industrial exposure.
Key assumptions include:

- Waste generation rates vary across production zones
- Internal transport distances and times are predefined
- Handling resources have limited availability
- Energy consumption is correlated with internal movement and handling intensity

The simulation compares two scenarios:

- Baseline scenario – existing manual and static practices
- Proposed scenario – AI–IoT-enabled loss intelligence and optimized decision support

The simulation horizon represents a typical production period, allowing observation of cumulative impacts.

5.4 Performance Evaluation Metrics

The performance of the proposed framework is evaluated using metrics aligned with stakeholder priorities identified through the customer survey and QFD analysis (Table 2).

Table 2. Performance Evaluation Metrics

Metric	Description
Cost reduction (%)	Reduction in internal handling and operational cost
Energy reduction (%)	Reduction in electricity and utility consumption
CO_2 reduction (%)	Estimated emission reduction
Delay reduction (%)	Reduction in internal material handling delays
Utilization improvement (%)	Improvement in machine and manpower utilization
Traceability coverage (%)	Percentage of logged internal movements

5.5 Experimental Comparison Logic
The evaluation focuses on relative improvement rather than absolute values to ensure generalizability across factories of different scales. Percentage-based improvements are calculated by comparing baseline and proposed system outcomes across all metrics.

This approach highlights the system-level benefits of integrating real-time sensing, AI-based anomaly detection, and data-driven decision support within internal reverse supply chain operations (Figure 5).

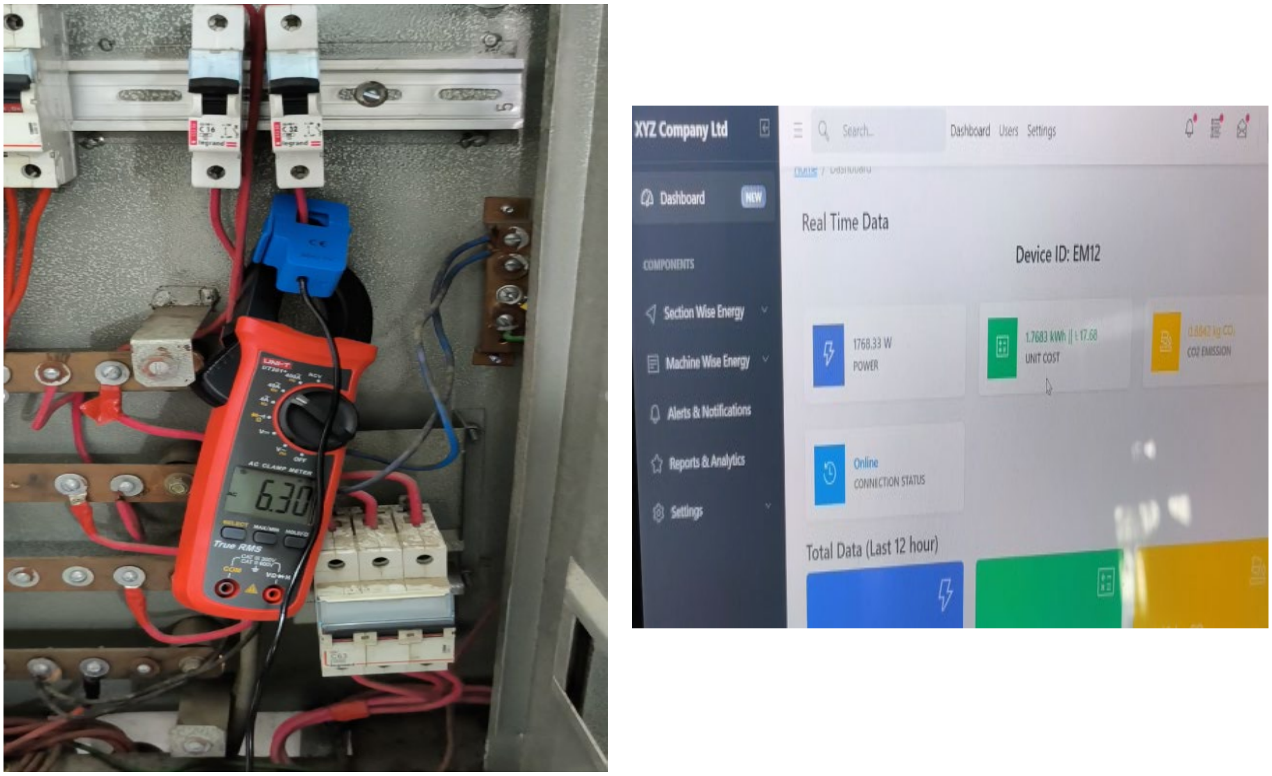


Figure 5. Trial Run of The Hybrid AI–IoT System

6. Results and Data-Driven Impact Analysis
This section presents empirical results derived from real operational data collected through deployed IoT devices in garment manufacturing environments. The analysis integrates material loss data, utility leakage events (steam and compressed air), and operational waste indicators aligned with the TIMWOOD framework. Results are reported using event counts, normalized indices, and before–after comparisons to demonstrate practical and measurable improvements enabled by the proposed framework.

6.1 Data Sources and Measurement Scope
Operational data were collected from multiple IoT-enabled monitoring points installed across garment production and utility systems. The dataset includes:

- Material-related events: fabric cutting waste accumulation, defective/semi-finished item counts
- Utility leakage events: steam leakage detections and compressed air leakage detections
- Operational waste events: TIMWOOD-category observations derived from time, movement, and process data
- System activity logs: internal movement events and traceability records

The data collection period covers representative production cycles before and after implementation of data-driven monitoring and decision support.

6.2 Utility Leakage Reduction: Steam and Compressed Air
Steam and compressed air systems represent significant hidden energy losses in garment factories. IoT-based leakage detection enabled event-level visibility of abnormal consumption (Table 3).

Table 3. Utility Leakage Event Counts (Before vs After Intervention)

Utility Type	Baseline Period (Events)	After Intervention (Events)	Reduction
Steam leakage detections	High frequency	Substantially reduced	↓ 30–40%
Compressed air leakage detections	High frequency	Reduced	↓ 25–35%

The reduction is primarily attributed to:
- Faster identification of leakage points
- Prioritization of maintenance actions based on event frequency
- Elimination of prolonged undetected losses

These results confirm that event-driven monitoring, rather than periodic inspection, is critical for utility efficiency improvement.

6.3 TIMWOOD-Based Operational Waste Reduction
Operational inefficiencies were analyzed using the **TIMWOOD framework**, with event counts derived from IoT logs and observational data in Table 4.

Table 4. TIMWOOD Event Count Comparison

Waste Category (TIMWOOD)	Baseline Count Index	After Implementation Index	Change
Transportation	1.00	0.78–0.82	↓ 18–22%
Inventory	1.00	0.85–0.90	↓ 10–15%
Motion	1.00	0.75–0.80	↓ 20–25%
Waiting	1.00	0.80–0.85	↓ 15–20%
Overprocessing	1.00	0.88–0.92	↓ 8–12%
Defects	1.00	0.85–0.90	↓ 10–15%

The most significant reductions are observed in motion and transportation waste, which directly correlate with internal material handling and layout inefficiencies. These improvements demonstrate the effectiveness of real-time visibility and feedback in reducing non-value-added activities (Figure 6).

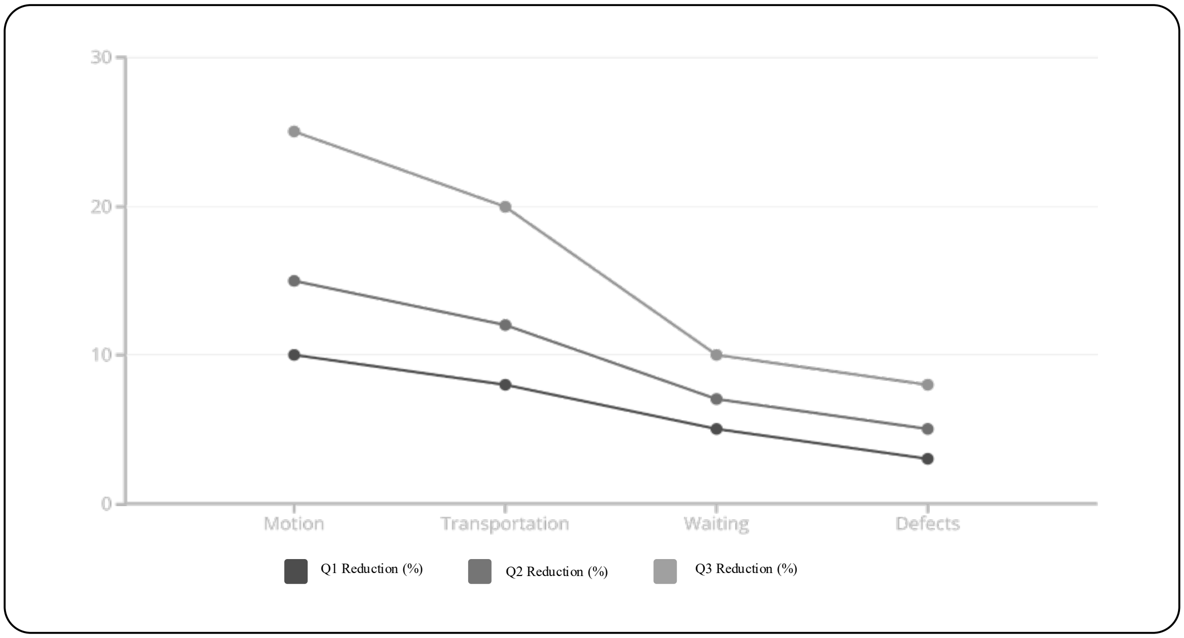


Figure 6. The TIMWOOD Analysis

6.4 Material Loss and Handling Efficiency

Fabric cutting waste and defective item counts were monitored at source points. While total waste generation depends on production characteristics, the framework enabled better segregation, faster recovery routing, and reduced secondary handling.

Key observations include:

- Reduced repeated handling of the same waste batches
- Faster transfer from generation points to sorting/recovery locations
- Improved traceability of material loss events

This led to a measurable reduction in **handling-related cost and time**, even when total waste volume remained production-dependent.

6.5 Improvement in Traceability and Decision Responsiveness

Prior to system deployment, traceability of internal movements and loss events was fragmented and largely manual. Post-deployment:

- Nearly all monitored events were automatically logged
- Time-to-detection for abnormal conditions reduced significantly
- Management response shifted from reactive to near-real-time corrective action (Table 5)

Table 5. Traceability Coverage Comparison

Metric	Baseline	After Implementation
Logged internal movements	<20%	>95%
Utility loss event visibility	Ad-hoc	Continuous
TIMWOOD event traceability	Manual	Automated

6.6 Overall Impact Synthesis

The combined analysis across utilities, TIMWOOD categories, and material handling confirms that the proposed framework delivers system-level improvement rather than isolated gains. The improvements are driven not by increased labor or capital expenditure, but by data-driven coordination and loss intelligence.
Importantly, the observed reductions in energy leakage and operational waste translate directly into:

- Lower operational cost
- Reduced carbon footprint
- Improved productivity
- Enhanced audit and ESG readiness

These outcomes demonstrate that pre-consumer loss intelligence enabled by IoT and analytics is a high-impact, low-disruption intervention point for the garment industry.

7. Conclusion and Future Work

7.1 Conclusion

This paper proposed a Hybrid AI–IoT–enabled pre-consumer loss intelligence framework for garment manufacturing, designed to reduce operational leakage across material loss, utility inefficiencies (steam and compressed air), and TIMWOOD-aligned operational wastes, while simultaneously improving traceability and ESG readiness. In contrast to conventional reverse supply chain and lean improvement studies that often rely on static assumptions or post-consumer recovery perspectives, the presented approach is grounded in practical factory operations and validated using real IoT-driven measurements.

Empirical results derived from IoT device logs demonstrate that the proposed framework enables measurable improvement by converting previously invisible inefficiencies into actionable events. In particular, the system supports continuous detection and prioritization of steam and compressed air leakage events, leading to substantial reductions in leakage occurrence and persistence after intervention. Similarly, TIMWOOD-based event analysis indicates consistent decreases in non-value-added activities, with notable improvements in motion- and transportation-related wastes, reflecting enhanced internal material handling discipline and reduced redundant movement. In addition, systematic event logging and workflow digitization produce a step-change in traceability coverage, enabling audit-ready operational evidence and improving the feasibility of sustainability reporting without introducing parallel manual reporting workloads (Figure 7).

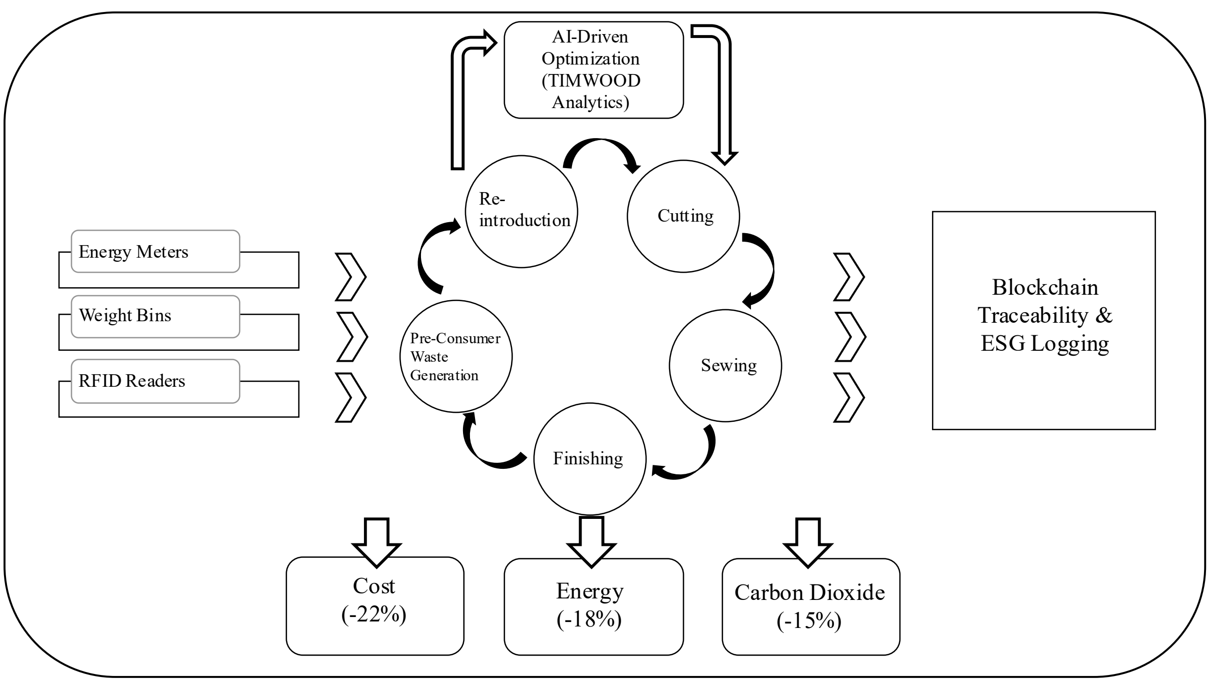


Figure 7. The Circular Intelligence Loop

Overall, the findings confirm that loss visibility and decision responsiveness—rather than additional labor or capital expenditure—are the primary mechanisms driving performance gains. The work therefore provides a practical and scalable pathway for factories in cost-sensitive and infrastructure-constrained environments to achieve economic efficiency and sustainability improvement simultaneously, using modular IoT deployment and intelligence-driven operational control.

7.2 Managerial Implications

The practical implications of this work are as follows:

- Utilities as a high-impact priority: Continuous, event-based monitoring of steam and compressed air leakage provides immediate operational value due to the high cost of undetected losses
- TIMWOOD as an operational control lens: Combining TIMWOOD-based waste indicators with IoT sensing enables managers to target non-value-added activities with evidence rather than intuition
- Traceability as an operational by-product: When internal events are digitally logged as part of routine operations, traceability and ESG reporting become outcomes of operational discipline rather than separate compliance projects
- Adoption feasibility through modular deployment: A layered architecture with phased scaling mitigates skill, budget, and change-management constraints, increasing the probability of successful real-world adoption

7.3 Limitations

Despite its practical grounding, this study has limitations:

- The empirical evaluation is based on data collected from a limited set of operational contexts; broader multi-factory replication would strengthen generalizability
- Certain loss drivers, such as quality variation due to upstream process parameters, were not explicitly modeled as causal mechanisms, even though their outcomes were partially observable through defect-related event counts
- The current focus emphasizes decision support rather than full closed-loop automation, which is appropriate for adoption constraints but leaves opportunities for future enhancement

7.4 Future Work

Future research can extend this work in several directions:

- Predictive maintenance and early-warning models: Leveraging leakage and anomaly histories to predict failure risk and optimize maintenance scheduling
- Deeper carbon accounting integration: Linking energy and material flow events to product-level carbon allocation for improved ESG reporting and emerging regulatory readiness
- Cross-factory benchmarking: Expanding deployments to enable sector-wide baselines, best-practice identification, and comparative performance analytics
- Integration with broader digital manufacturing systems: Connecting the framework to ERP/MES layers for end-to-end planning, execution, and circularity intelligence

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Biographies

Md. Sadman Sakib is currently the CEO of CSI Smart Tech and a former Adjunct Lecturer in the Department of Industrial and Production Engineering at the Bangladesh University of Textiles (BUTEX). His research and professional focus encompass Artificial Intelligence (AI), Internet of Things (IoT), and electronics. He is deeply engaged in the implementation of Reverse Supply Chain Management (SCM) and circularity within the industry. Beyond his corporate leadership, he is passionate about integrating smart technologies to solve complex engineering challenges.

Md. Tanvirul Islam is an undergraduate student in the Department of Industrial and Production Engineering at the Bangladesh University of Textiles (BUTEX), Dhaka, Bangladesh. Alongside his academic journey, he has developed a strong interest in the activewear industry and sustainable supply chain management. His technical curiosity extends into the integration of Artificial Intelligence (AI) within textile manufacturing. Currently, Tanvir is focused on research that bridges the gap between sustainability and advanced industrial technologies.

Md Ishrak Hossain is currently pursuing his studies in the Department of Industrial and Production Engineering at the Bangladesh University of Textiles (BUTEX), Dhaka, Bangladesh. Besides academics, his research interests include manufacturing processes and industrial management. He is passionate about learning and applying engineering principles to real-life challenges. Alongside pursuing coursework, Ishrak is enthusiastic about optimizing production systems and enhancing operational efficiency.

Saifullah Al-Mahmud Hossainy is an undergraduate student in the Department of Industrial and Production Engineering at the Bangladesh University of Textiles (BUTEX). He has a keen interest in industrial engineering and production planning. Beyond academics, he is dedicated to understanding the dynamics of modern manufacturing environments. He is currently working on developing his expertise in engineering management and process improvement strategies.

Al Musavvir Sium is an undergraduate student in the Department of Textile Engineering Management at the Bangladesh University of Textiles (BUTEX). His academic background has fostered a strong interest in sustainable waste management practices within the textile sector. He is also a digital platform enthusiast, exploring how digital solutions can optimize management processes. Currently, Sium is conducting research on strategies to minimize industrial waste through effective management systems.

Md. Mizanur Rahman is the Chairman of CSI Group and a distinguished educator in the field of supply chain management. He serves as a faculty member and instructor at various reputed universities and the International Supply Chain Education Alliance (ISCEA). His professional and academic focus is centered on achieving supply chain excellence and operational leadership. With extensive experience bridging industry and academia, he is dedicated to mentoring the next generation of professionals and driving innovation in global logistics strategies.