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Artificial Intelligence and Sustainable Operations: A Framework for Healthcare Equipment Manufacturing Industry

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Abstract

Healthcare equipment manufacturing faces the dual imperative of maintaining product safety, regulatory compliance and quality while advancing sustainability across the product life cycle. This review conceptualizes artificial intelligence as a set of operational capabilities that can enhance predictive maintenance, process optimization, quality assurance, traceability, demand planning, circular design and life-cycle decision-making. At the same time, the paper shows that AI can create new sustainability problems through high computing demand, data governance burdens and regulatory complexity if adoption is poorly designed (Katirai, 2024; Rowan, 2024; Bignami et al., 2025). [1]

The paper uses a PRISMA-informed systematic literature review, structured through SPAR-4-SLR logic and thematic analysis. The final corpus included 58 peer-reviewed publications from 2000 to June 2026, with a strong concentration after 2020, alongside selected policy and sector documents for contextual support on regulation and net-zero supply chains (Page et al., 2021; Paul et al., 2021). [2]

The literature reveals six consistent findings: AI-enabled predictive maintenance reduces downtime, energy loss and unnecessary component replacement; digital twins enhance process visibility, design iteration and resource efficiency; AI-based quality systems support defect, scrap and compliance-risk reduction; circular economy models for medical devices are technically feasible but operationally underdeveloped; healthcare supply chains remain a major sustainability hotspot, highlighting the value of AI-enabled procurement and inventory management; and sector-specific evidence remains fragmented, with limited plant-level empirical research focused directly on healthcare equipment manufacturing. The main research gap, therefore, is not whether AI can support sustainable operations, but how to govern, validate and scale it in tightly regulated manufacturing environments without shifting environmental and ethical burdens elsewhere. [3]

Introduction and Background

Healthcare systems have a substantial environmental footprint, and a large share of that footprint sits in purchased goods and supply chains rather than only in hospital buildings or clinical energy use. Medical devices and healthcare products therefore matter not just because they improve care, but because they shape emissions, materials use, waste generation, product longevity and procurement choices across the health sector. Global work on healthcare sustainability has shown that supply chains are among the biggest sources of healthcare emissions, while NHS policy has moved from general sustainability goals to supplier-facing net-zero requirements that increasingly affect device makers and service providers (MacNeill et al., 2020; Lenzen et al., 2020; NHS

England, 2026). For healthcare equipment manufacturers, sustainability is no longer a side issue. It is becoming part of market access, procurement evaluation and long-term competitiveness. [4]

Problem statement. The healthcare equipment manufacturing industry faces a hard operational balance. Firms must meet strict standards for sterility, reliability, validation, documentation, cybersecurity and post-market performance, while also responding to pressure for lower carbon products, lower waste, more reuse, circular business models and more resilient supply chains. Traditional improvement tools help, but the scale and speed of the challenge increasingly require data-rich decision systems. AI has emerged as one of the most discussed technologies in this space because it can process sensor data, forecast failure, detect anomalies, optimise schedules, support traceability and improve product and process design. However, the evidence base is scattered. Many studies focus on clinical AI, software as a medical device, or general sustainable manufacturing, while far fewer studies examine the operational core of healthcare equipment manufacturing plants and their upstream networks (Rowan, 2024; Han et al., 2024; Zhou & Gattinger, 2024; Espinosa et al., 2026). [5]

Relevance of AI to sustainability in healthcare manufacturing. AI matters in this sector because sustainability problems are operational problems. Energy spikes come from poorly tuned processes and idle equipment. Scrap comes from unstable quality and imperfect inspection. Waste grows when maintenance is reactive, inventory is inaccurate, products are designed for one-way use, or reverse flows are absent. Supply risk rises when manufacturers cannot see demand shifts, component bottlenecks or compliance issues early enough. AI can improve these levers through predictive maintenance, machine vision, digital twins, intelligent scheduling, demand forecasting, process learning and life-cycle optimisation. Yet the same literature also warns that AI systems can add hidden environmental costs through data storage, training energy, hardware turnover and opaque governance. In healthcare manufacturing, this trade-off is even sharper because inaccurate models can create both environmental waste and patient safety risks (Katirai, 2024; Rojek et al., 2026; Ahangar et al., 2025). [6]

Research scope. This paper defines healthcare equipment manufacturing broadly. It includes producers of medical devices, diagnostics, imaging systems, hospital consumables, connected devices and related components, as well as the manufacturing, quality, logistics and life-cycle systems that support them. The focus is on operations rather than on purely clinical AI. Accordingly, the review includes literature on sustainable manufacturing, medical device circularity, healthcare procurement, life-cycle assessment, predictive maintenance, digital twins, AI-enabled quality systems and manufacturing supply chains. It does not attempt to review all clinical AI applications, and it excludes studies that are clinically relevant but operationally unrelated to manufacturing. Because the field is still emerging, the paper also draws on adjacent literature from smart manufacturing and healthcare product life-cycle management where those findings are transferable to healthcare equipment manufacturing. This wider but disciplined scope is necessary because the exact niche remains under-researched even as sector demand is expanding rapidly (Rowan, 2024; MacNeill et al., 2020; Fianko et al., 2026). [7]

Research Methodology

This paper uses a **systematic literature review** because the topic is interdisciplinary, fast-moving and conceptually fragmented. A narrative review would have been too vulnerable to selection bias,

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while a statistical meta-analysis would have been unsuitable because the studies differ widely in design, unit of analysis and outcome measures. A PRISMA-informed review design was therefore combined with SPAR-4-SLR logic and thematic analysis. PRISMA improved transparency in identifying, screening and reporting the literature, while SPAR-4-SLR was useful because the topic spans management, operations, engineering and healthcare policy rather than one single discipline (Page et al., 2021; Tranfield et al., 2003; Denyer & Tranfield, 2009; Paul et al., 2021). [8]

Justification for research design. The review asked one central question: *How does AI support sustainable operations in the healthcare equipment manufacturing industry, and what gaps prevent wider operational adoption?* This question required three forms of synthesis. First, it requires a process view of manufacturing operations such as maintenance, quality, design, planning and logistics. Second, it required a sustainability view that covered environmental, economic and governance outcomes. Third, it required a healthcare-specific view because medical products face stricter regulatory and safety requirements than many other manufactured goods. A systematic review could bring these streams together more reliably than a purely conceptual essay. Thematic analysis was selected for interpretation because the corpus included review papers, empirical articles, case analyses, regulatory reviews, life-cycle studies and design papers, which are not directly comparable in a single statistical framework (Kiger & Varpio, 2020; Braun & Clarke, 2022). [9]

Data sources and search strategy. Searches were conducted across PubMed, PubMed Central, publisher databases and indexed article pages from Springer, MDPI, Frontiers, BMJ, Health Affairs, Elsevier-linked abstracts and related scholarly sources. The search window covered January 2000 to June 2026, with stronger weighting given to 2020–2026 because AI-enabled manufacturing and sustainable healthcare operations accelerated during that period. Core search strings combined variations of the following terms: “artificial intelligence”, “machine learning”, “deep learning”, “digital twin”, “predictive maintenance”, “quality monitoring”, “sustainable manufacturing”, “circular economy”, “life cycle assessment”, “medical device”, “healthcare equipment”, “hospital products”, and “healthcare supply chain”. Backward snowballing from key review papers was then used to identify foundational works on medical device circularity, sustainable design and systematic review methods. The final sample included **58 peer-reviewed papers**, supplemented by a small number of official sources from the FDA, NHS and international health sustainability bodies used only to frame sector context. [10]

Inclusion and exclusion criteria. Included studies had to meet four conditions: they were peer-reviewed and published; they were available in English; they addressed either AI in manufacturing/supply-chain operations, sustainability in healthcare products or medical devices, or a clear intersection of both; and they had direct relevance to operational decisions in product design, production, maintenance, logistics, quality, reuse or life-cycle management. Studies were excluded if they focused only on clinical diagnosis without an operations link, were purely promotional or non-peer-reviewed, lacked sufficient methodological or conceptual substance, duplicated better versions of the same work, or had been retracted. One 2023 healthcare supply chain AI article was identified during screening but excluded because it was later formally retracted in 2026. [11]

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Data analysis. The retained corpus was coded in two rounds. In the first round, each paper was classified by domain, method and operational focus. In the second, the papers were grouped into six thematic clusters: predictive maintenance and asset efficiency; digital twins and real-time process visibility; AI-enabled quality, compliance and trust; circularity and life-cycle sustainability of medical devices; supply chain, procurement and resilience; and design, additive manufacturing and product innovation. The synthesis then examined how each cluster affected the three sustainability dimensions most relevant to operations: environmental performance, economic performance and governance or compliance performance. Because the studies were heterogeneous, the review did not estimate pooled effect sizes. Instead, it used pattern matching and thematic synthesis to identify converging findings, contradictions and underdeveloped areas. [12]

Review element	Choice used in this paper
Review approach	PRISMA-informed systematic literature review with SPAR-4-SLR logic
Time window	2000 to June 2026, with emphasis on 2020–2026
Final review corpus	58 peer-reviewed papers
Context sources	Selected official materials from FDA, NHS and healthcare sustainability bodies
Main analytical technique	Thematic analysis and pattern synthesis
Core operational themes	Maintenance, quality, digital twins, circularity, supply chain resilience, additive manufacturing and design
Unit of interpretation	Sustainable operations in healthcare equipment manufacturing and adjacent medical device systems

The methodology choices are consistent with current best practice in systematic review design and with the mixed engineering-management nature of the topic. [13]

Comprehensive Literature Review

The reviewed literature shows that AI contributes to sustainable operations through a set of connected managerial and technical mechanisms rather than through one isolated tool. Across the corpus, the strongest themes were predictive maintenance, digital twins, quality control, circular device systems, supply chain intelligence and AI-enabled design. The table below maps the most relevant strands of literature for this paper.

Theme	AI Features	Sustainability	References
Predictive maintenance and asset health	Sensor analytics, anomaly detection, remaining useful life estimation, maintenance scheduling	Lower downtime, lower spare-part waste, longer equipment life, lower energy losses	(Çınar et al., 2020; Pech et al., 2021; Achouch et al., 2022; Abidi et al., 2022; Jasiulewicz-Kaczmarek et al., 2024; Bitam et al., 2025)

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Theme	AI Features	Sustainability	References
Digital twins and smart factories	Virtual replicas, simulation, process visibility, decision support	Better process control, lower trial-and-error waste, improved throughput, improved resource planning	(Huang et al., 2021; Wang et al., 2022; Yao et al., 2023; Lv et al., 2023; Rowan, 2024; Omigbodun, 2026)
Sustainable manufacturing systems	Process optimisation, assembly-line learning, intelligent scheduling, energy analytics	Reduced waste, better line balance, improved energy efficiency, better productivity-sustainability balance	(Jamwal et al., 2021; Jamwal et al., 2022; Sahoo et al., 2023; Hijry, 2026; Martínez et al., 2026; Lazarević & Obrecht, 2026; Rojek et al., 2026)
Circularity and medical device life cycles	Design-for-reuse, product-service systems, recovery loops, lifecycle evaluation	Longer product use, less landfill, better procurement decisions, reduced material intensity	(Messelbeck & Sutherland, 2000; Hanson & Hitchcock, 2009; Guzzo et al., 2020; MacNeill et al., 2020; Harkin et al., 2024; Martin et al., 2025)
Life-cycle assessment and reuse decisions	Comparative environmental modelling, cost and emissions analysis	Better choice between single-use and reusable products, visibility of hidden carbon hotspots	(Rizan et al., 2020; Robinson et al., 2023; Sharma et al., 2024; Thiel et al., 2024; Thöne et al., 2024; Booth et al., 2025)
Supply chains, regulation and trust	Forecasting, inventory planning, digital traceability, explainability, regulatory alignment	Less stock waste, more resilience, better compliance, safer scale-up of AI-enabled products	(Kumar et al., 2023; Arji et al., 2023; Harvey & Gowda, 2020; Han et al., 2024; Zhou & Gattinger, 2024; Kaladharan et al., 2024; Muehlematter et al., 2024; Almarie et al., 2025; Ahangar et al., 2025; Ahangar et al., 2026; Espinosa et al., 2026)
Additive manufacturing and AI-enabled design	Design optimisation, generative support, process control, material efficiency	Lower prototyping waste, personalised and low-volume production, stronger circular design logic	(Mamo et al., 2023; Filippi et al., 2025; Tănase et al., 2025; Fianko et al., 2026; Li et al., 2026)

Table shows that literature is broad enough to identify recurring mechanisms, but it also shows why this field remains fragmented: only a smaller portion of the work is directly centred on

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healthcare equipment factories themselves. Much of the evidence comes from adjacent smart manufacturing studies or from the life-cycle and procurement side of medical devices. [14]

A first major stream concerns **predictive maintenance**. The manufacturing literature is clear that AI-based predictive maintenance supports sustainability by replacing time-based maintenance with condition-based intervention. This reduces unnecessary replacements, prevents catastrophic failures, cuts energy losses from degraded machinery and can improve overall equipment effectiveness. Reviews by Çınar et al. (2020) and Achouch et al. (2022) describe how machine learning can support fault diagnosis, anomaly identification and useful-life prediction in Industry 4.0 systems. Pech et al. (2021) add the role of intelligent sensors, while Abidi et al. (2022) show how predictive planning can be built into broader decision models. For healthcare equipment manufacturing, these findings are important because unplanned downtime does not only raise costs; it can interrupt tightly validated production sequences, increase scrap and threaten delivery of critical devices. More recent work links Maintenance 4.0 explicitly to sustainable manufacturing, reinforcing the idea that maintenance quality has direct environmental implications (Jasiulewicz-Kaczmarek et al., 2024; Bitam et al., 2025). [15]

A second stream focuses on **digital twins and real-time process visibility**. Digital twin research has matured from conceptual discussion to detailed review work. Huang et al. (2021) characterise AI-driven digital twins as a foundation for smart manufacturing and robotics. Yao et al. (2023) show the breadth of applications, while Wang et al. (2022) extend the idea from the factory to the supply chain. Rowan (2024) is especially important for this paper because the review is one of the clearest efforts to connect digital twins and extended reality to safe and sustainable opportunities in medical device and healthcare sectors. Omigbodun (2026) further links AI-driven digital twins to sustainable manufacturing performance. In practical terms, digital twins can help device manufacturers reduce material waste during process tuning, simulate design alternatives before physical trials, improve energy-aware scheduling and support more robust change control. For regulated environments, they also create a stronger evidence trail when process adjustments must be documented and validated. [16]

A third-stream concerns **AI-enabled quality systems and trustworthy governance**. Quality failures in healthcare equipment manufacturing carry higher stakes than in many consumer industries. Scrap recalls and rework waste materials and energy, but they can also create patient harm and regulatory action. This explains why literature increasingly joins AI performance to explainability and trustworthiness. Ahangar et al. (2025) argues that transparency, fairness, robustness and accountability are now central adoption conditions in manufacturing. Their 2026 study on explainable AI in quality and condition monitoring moves the discussion from abstract principles to practical monitoring use cases. This is consistent with the medical-device regulatory literature. Harvey and Gowda (2020), Han et al. (2024), Zhou and Gattinger (2024), and Kaladharan et al. (2024) all show that regulation of AI-enabled medical technologies still struggles with adaptive learning, transparency, data diversity and lifecycle control. The implication for sustainable operations is straightforward: manufacturers will not sustain AI adoption unless model behaviour can be validated, audited and integrated with quality systems. A technically accurate model that cannot be trusted or explained may create more rework, delay and compliance burden than benefit. [17]

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A fourth stream addresses **circularity and life-cycle sustainability in medical devices**. This is where healthcare-specific literature becomes strongest. Guzzo et al. (2020) identified circular business model paths in the medical device industry, while MacNeill et al. (2020) argued for a broader road map to a circular economy in medical devices. Earlier design work by Messelbeck and Sutherland (2000) and Hanson and Hitchcock (2009) already showed that sustainability concerns in biomedical products are not new, but recent work has made them more operational. Harkin et al. (2024) review lifecycle evaluation models for medical devices, and Martin et al. (2025) show how environmentally responsible use can be studied at the level of infusion systems. The cumulative message is that circular logic in healthcare equipment manufacturing depends on far more than recycling. It depends on design for durability, modularity, serviceability, refurbishment, recovery logistics and procurement models that value long-term performance rather than lowest first cost. AI can support these changes through better failure prediction, usage analytics, digital passports, traceability and reverse logistics planning, but the literature shows that these applications are still under-developed in medical device factories. [18]

A fifth stream comes from **life-cycle assessment and the single-use versus reusable debate**. Healthcare manufacturers often work in markets where single-use products have been favoured for sterility, convenience and speed. Yet LCA studies reveal that the sustainability case is rarely simple. Rizan et al. (2020) showed wide carbon variation across surgical operations. Thiel et al. (2024) identified major radiology carbon hotspots, especially from equipment energy use. Thöne et al. (2024) found materially higher environmental and health impacts for single-use flexible ureteroscopes compared with reusable alternatives. Booth et al. (2025) and Robinson et al. (2023) reinforce the need for updated, context-specific environmental comparisons, while Sharma et al. (2024) demonstrates the growing use of LCA methods across healthcare. For manufacturers, these studies matter because they change operational priorities. Sustainable operations are not limited to greener factories; they also depend on what the factory produces, how long products last, how they are reprocessed and how environmental burdens move across use and end-of-life stages. AI can improve these decisions by surfacing hidden hotspots, optimising design choices and linking product use data back to redesign. [19]

A sixth stream concerns **supply chains, procurement and resilience**, which are critical in healthcare equipment manufacturing because the industry often relies on specialised inputs, validated suppliers and regulated distribution channels. Kumar et al. (2023) identify critical success factors for AI adoption in healthcare supply chains. Arji et al. (2023) show that AI, blockchain, big data and simulation were important digital tools in managing healthcare supply disruptions during COVID-19. Moosavi et al. (2022) link resilience and sustainability in broader disruption strategy, while Espinosa et al. (2026) argue that AI's potential in healthcare supply chains is still underused. These studies fit well with sector policy pressure. The NHS supplier roadmap and broader healthcare decarbonisation discussions show that device makers and suppliers are increasingly expected to provide better traceability, lower emissions and stronger operational resilience at the same time. AI can support forecasting, inventory optimisation, supplier risk analysis and waste reduction, but healthcare-specific deployment studies remain limited. [20]

Finally, the literature on **AI-enabled design, additive manufacturing and innovation** adds a forward-looking dimension. Mamo et al. (2023) review biomedical 3D printing, while Filippi et

International Journal of Business and Economics
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Vol. 26, No. 1, 2026
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al. (2025) connect biofabrication to AI-driven predictive methods and sustainability. Tănase et al. (2025) map AI in biomedical 3D printing; Fianko et al. (2026) reviews AI as an enabler of sustainable additive manufacturing; and Li et al. (2026) examines sustainable industrial design through a technology-system-institution lens. These studies suggest that AI can support more material-efficient prototyping, design for customisation, low-volume medical production and stronger alignment between design choices and life-cycle impact. This is especially relevant in healthcare equipment manufacturing because product variety is high, validation costs are meaningful and customisation is often clinically valuable. Still, the literature remains heavier on review and conceptual work than on full-scale industrial evidence. [21]

Theoretical Underpinning

This study is theoretically grounded in Dynamic Capabilities Theory, which explains how firms adapt, integrate and reconfigure internal and external resources to respond to changing environments. In the context of healthcare equipment manufacturing, AI can be viewed as a dynamic capability that enables firms to sense operational inefficiencies, seize improvement opportunities and transform manufacturing, quality, supply chain and life-cycle processes toward more sustainable outcomes (Teece, Pisano, & Shuen, 1997; Teece, 2007).

Findings and Research Gaps

The first clear finding is that **AI supports sustainability most convincingly when it is tied to concrete operational problems** rather than broad digital transformation rhetoric. Predictive maintenance, machine vision inspection, digital twins and AI-assisted planning show the strongest operational logic because they attack visible sources of cost and waste at the same time. In healthcare equipment manufacturing, this matters because downtime, rework and inventory obsolescence are expensive and can also raise environmental burdens. The literature therefore supports a practical claim: the best sustainability gains are likely to come from AI used in asset health, process control and quality systems before moving to more speculative use cases. [22]

The second finding is that **healthcare sector specificity changes the AI sustainability equation**. In many manufacturing industries, firms can optimise quickly and iterate in production. In healthcare equipment manufacturing, changes must fit quality systems, design controls, validation records and regulatory expectations. This slows AI absorption but also makes trustworthy AI more valuable. Explainability, auditability and lifecycle control are not optional extras here; they are part of operational feasibility. That is why regulatory and trust literature is so important to sustainable operations in this sector. An energy-saving algorithm that cannot be validated in a regulated environment is unlikely to be sustained. [23]

The third finding is that **literature increasingly treats sustainability as a life-cycle issue rather than a factory-only issue**. Circular medical device studies, infusion-system reviews and comparative LCA papers show that product choice, reuse pathways, reprocessing requirements and end-of-life design can dominate the environmental profile of healthcare products. This pushes manufacturers to think beyond emissions within the plant. Sustainable operations now include product architecture, refurbishment capacity, digital traceability, service-based business models and procurement collaboration with hospitals. AI can support this broader model, but the empirical

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healthcare manufacturing literature is still not mature enough to show how these systems scale in practice. [24]

The fourth finding is that **supply chains are a decisive but under-examined lever**. Healthcare manufacturing cannot be sustainable if suppliers, validated components, transport routes and hospital-side ordering remain opaque. The latest healthcare supply chain reviews show rising interest in AI for resilience but also confirm that the field is still underdeveloped. This is important because supply chain emissions are often larger than operational emissions, and because device makers are increasingly judged on supplier practices and scope 3 performance. AI-based demand sensing, supplier risk scoring and digital documentation are therefore likely to become more central than they appear in today's manufacturing-focused literature. [25]

The fifth finding is a cautionary one: **AI can shift environmental burdens instead of removing them**. Katirai (2024) and Bignami et al. (2025) remind us that AI itself has an environmental cost, especially when compute-intensive models, redundant data retention and frequent hardware refreshes are ignored. For healthcare equipment manufacturers, this means that not all AI is automatically "green". The sustainability value of AI depends on proportionality. Lightweight models that cut rework or extend equipment life may deliver strong net benefits. Overbuilt models with weak operational use may simply add digital overhead. Future operational studies need to report both the savings created by AI and the resources consumed by AI systems themselves. [26]

The table below summarises the main research gaps that emerge from the review.

Gap area	What the literature currently shows	Why the gap matters for healthcare equipment manufacturing
Direct plant-level evidence	Many reviews and conceptual papers; fewer empirical studies from regulated healthcare equipment factories	Limits confidence about real savings, validation burden and scale-up pathways
Sustainability metrics	Studies use different indicators: carbon, waste, downtime, energy, cost, resilience and quality	Makes comparison difficult and weakens business-case translation
AI system footprint	Environmental savings are often discussed, but model energy and data footprint are rarely measured	Risks burden shifting and weak net sustainability gains
Circular implementation	Good conceptual work on circular medical devices exists, but reverse logistics and refurbishment evidence is thin	Circular models cannot scale without operational proof
Governance and trust	Regulation is well discussed for AI-enabled devices, less so for AI used inside manufacturing operations	Creates uncertainty for quality, validation and audit teams

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Gap area	What the literature currently shows	Why the gap matters for healthcare equipment manufacturing
Healthcare supply chain integration	AI adoption studies exist, but many are still generic or early stage	Scope 3 emissions and resilience pressures require more sector-specific evidence
Human factors and skills	Technical papers dominate; worker capability, acceptance and redesign of roles are less studied	Sustainable adoption needs operators, engineers, quality staff and procurement teams to work with AI

This gap pattern suggests that the field is moving from “can AI help?” to “under what operational, regulatory and environmental conditions does AI help enough to justify adoption?” That is a much more useful research question for both scholars and industry. [27]

A stronger future agenda would therefore include longitudinal studies from medical device plants, hybrid evaluations that combine operational KPIs with LCA data, comparative studies across reusable and single-use product classes, and governance studies linking manufacturing AI to ISO-based quality systems and post-market surveillance. There is also room for research on small and medium-sized manufacturers, who may benefit substantially from AI but lack the data infrastructure and compliance resources of large multinational firms. In short, the present literature is strategically promising but operationally incomplete. [28]

Conclusion

AI has real potential to improve sustainable operations in healthcare equipment manufacturing, but its value is not automatic. The literature reviewed in this paper shows that the most credible benefits come from practical applications: predictive maintenance, AI-enabled quality assurance, digital twins, better planning, and stronger life-cycle visibility. These applications can lower downtime, reduce scrap, improve energy use, support regulatory discipline and make circular business models more realistic. They fit the needs of a sector where product failure is costly, regulation is strict and procurement is increasingly shaped by sustainability expectations. [29]

At the same time, the review also shows that the evidence base is still immature. Much of the current work remains review-led, adjacent to healthcare manufacturing rather than centred on it, or focused on the product lifecycle outside the factory wall. The key challenge for the next phase is therefore implementation discipline: manufacturers need AI systems that are explainable, auditable, proportionate in energy use and aligned with validated operational processes. The central contribution of this paper is to show that sustainable operations in healthcare manufacturing should not treat AI as a generic digital trend. It should be treated as a carefully governed operational capability that supports safer products, lower-impact processes and more resilient supply networks. If that principle guides future research and industry practice, AI can become a meaningful enabler of sustainable healthcare manufacturing rather than just another layer of complexity. [30]

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