

Systematic Review

Artificial Intelligence and Sustainability Value Creation in Industry: A Systematic Literature Review and a Mechanism-Based Framework

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Abstract

Artificial intelligence (AI) is increasingly recognised as an enabler of sustainability in industrial systems, yet existing research remains fragmented and strongly oriented towards technical optimisation. This systematic literature review examines how AI-enabled sustainability value creation has been conceptualised through the analysis of 75 peer-reviewed articles published between 2020 and 2025. The findings reveal a rapidly expanding field, with 54% of the reviewed studies published in 2024–2025. However, the evidence remains concentrated at process and plant levels: 69% of studies focus on operational applications, and 72% adopt technical, simulation-based, optimisation-oriented, or model-development approaches. Prediction, optimisation, monitoring, adaptive control, and decision support emerge as the dominant AI-enabled mechanisms, while social, governance, resilience, and systemic transformation dimensions remain comparatively underexplored. The review further shows that the literature is stronger in documenting operational sustainability outcomes than in explaining how sustainability value becomes organisationally embedded and sustained across industrial systems. In response, this study proposes a mechanism-based framework linking organisational antecedents, AI-enabled mechanisms, operational transformation, sustainability outcomes, and contextual contingencies. The framework conceptualises AI-enabled sustainability value creation as an organisationally embedded, contingent, and multilevel process rather than a direct outcome of technological deployment alone.

Keywords: artificial intelligence; industrial systems; industrial sustainability; sustainability value creation; AI-enabled mechanisms



Academic Editor: Darjan Karabašević

Received: 8 June 2026

Revised: 27 June 2026

Accepted: 3 July 2026

Published: 8 July 2026

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1. Introduction

Artificial intelligence (AI) has become a central driver of industrial transformation by enabling new forms of prediction, optimisation, automation, and decision support. In industrial systems, its potential extends beyond operational efficiency and is increasingly associated with sustainability-related improvements, particularly in resource efficiency, circularity, emissions reduction, and sustainable manufacturing transitions [1–5].

Despite this growing interest, the literature on AI and sustainability in industrial systems remains conceptually fragmented [2,4]. Existing studies frequently examine specific applications or technical performance gains, but they less often integrate these insights into a broader understanding of how AI contributes to sustainability value creation across industrial systems [1,4,6]. This fragmentation is reinforced by the dispersion of relevant research across the sustainability, operations, manufacturing, digital transformation, and information systems literature.

This limitation is especially visible in the treatment of sustainability value. Much of the literature emphasises environmental and operational outcomes, such as energy efficiency, waste minimisation, process optimisation, and emissions reduction, while paying more limited attention to the mechanisms through which AI generates such outcomes and the organisational and contextual conditions that shape them [6,7]. As a result, the field still lacks a sufficiently structured explanation of how AI-enabled sustainability value creation unfolds across industrial settings [4,5,8].

Against this background, this article examines how the literature has explained AI-enabled sustainability value creation in industrial systems. Rather than focusing only on applications or outcomes, the study examines how AI-enabled sustainability value is generated and shaped across industrial contexts. The review is guided by the following research question: How has the literature explained AI-enabled sustainability value creation in industrial systems, and what conceptual patterns, gaps, and tensions characterise this field?

To answer this question, the study addresses three sub-questions:

RQ1. What are the main application domains in which AI is associated with sustainability in industrial settings?

RQ2. What types of sustainability value are reported in the literature, and through which mechanisms are they explained?

RQ3. What organisational, technological, and contextual conditions shape AI-enabled sustainability value creation, and what conceptual gaps remain in the field?

Beyond synthesising the literature, the review develops a mechanism-based framework for explaining how AI-enabled sustainability value creation emerges across industrial systems.

The remainder of the article is structured as follows. Section 2 presents the conceptual background on AI, sustainability, and industrial systems. Section 3 outlines the systematic literature review methodology. Section 4 reports the review results, beginning with a descriptive overview of the final corpus and then examining the findings across the analytical dimensions guiding the review. Section 5 discusses the principal interpretive patterns emerging from the literature together with the study's theoretical and practical implications, limitations, and future research directions. Section 6 concludes the article.

2. Conceptual Background

This section outlines the concepts guiding the review. Rather than treating AI as a stand-alone technological artefact, this article adopts a capability- and process-oriented perspective on AI-enabled sustainability value creation in industrial systems. This perspective helps explain where AI is applied, how sustainability value is generated, and which organisational and technological conditions shape the outcomes. In line with capability-based perspectives, particularly dynamic capabilities and resource orchestration, AI is understood here as a digitally enabled capability whose contribution depends on its integration into organisational routines, decision structures, and industrial processes rather than on technical functionality alone. A value-creation perspective also helps explain how AI-enabled mechanisms operate across application domains and under different conditions to generate sustainability-related outcomes.

2.1. AI in Industrial Systems: From Automation to Intelligent Capability

For the purposes of this review, industrial systems are understood as socio-technical configurations that combine physical assets, human resources, digital infrastructures, and organisational routines to transform inputs into value-added outputs across manufacturing, energy, logistics, and related industrial contexts [9]. Within these systems, AI is increasingly understood not merely as a set of computational techniques but as an enabling capability that can reshape industrial decision-making, operational control, and process improvement [1,2]. In industrial and manufacturing settings, AI is commonly associated with applications such as predictive maintenance, production planning, fault detection, quality control, and energy management, which may contribute to improved resource efficiency and operational performance.

However, the role of AI in industry should not be reduced to technical efficiency alone. Recent work on sustainable manufacturing innovation suggests that industrial transformation increasingly depends on the ability to combine technological capabilities with broader sustainability-oriented system design and value creation logics. From this perspective, AI can be interpreted as a value-enabling capability whose contribution depends not only on algorithmic performance but also on how it is embedded in industrial processes, organisational routines, and managerial decision structures [10,11].

This distinction is important because AI does not automatically generate sustainability improvements. Prior reviews indicate that only a minority of manufacturing studies explicitly frame sustainability or resource efficiency as the primary objective of AI deployment; in many cases, sustainability-related benefits appear as indirect or secondary effects of optimisation, monitoring, or control solutions [3]. Accordingly, AI should be understood less as a self-contained source of value and more as a capability that may enable sustainability value creation under specific organisational and contextual conditions [10]. This view positions AI as a contingent, capability-dependent enabler of sustainability rather than as an automatic source of environmental gains [3,10].

2.2. Sustainability Value in Industrial Systems

The concept of sustainability value extends beyond narrow efficiency gains and encompasses improvements across environmental, economic, social, and governance dimensions [5,12]. In industrial systems, environmental value is often reflected in outcomes such as higher energy and resource efficiency, emissions reduction, waste minimisation, and improved environmental performance [12]. Economic and operational value may involve cost reduction, process efficiency, productivity gains, and more adaptive production systems [5,12]. Although less frequently emphasised in the manufacturing literature, social and governance value may include safer working conditions, enhanced transparency, more responsible decision-making, stronger compliance, and improved accountability structures [12,13].

Building on this broader view, this article distinguishes between proximal and broader sustainability outcomes. Proximal outcomes refer mainly to operational and efficiency-related improvements at the process or plant level, such as reduced energy use, lower material waste, or improved process control. Broader outcomes refer to more integrated and multidimensional effects at the firm, network, or supply-chain level, such as circularity, resilience, decarbonisation trajectories, sustainable performance, or long-term adaptive business configurations [8,12,14]. This distinction is analytically useful because the existing literature often reports measurable operational gains while providing a weaker account of how such gains translate into broader forms of sustainability value over time [8,15]. Sustainability value should be understood not as a single outcome category but as a layered construct that may emerge unevenly across different levels of industrial analysis.

In practice, sustainability performance in industrial systems is commonly tracked through indicators such as energy consumption per unit of output, greenhouse gas emissions intensity, material waste rates, and water usage. Broader sustainability objectives increasingly include long-term decarbonisation trajectories, circularity, organisational resilience, and alignment with frameworks such as SDG 9, SDG 12, and SDG 13 [16].

2.3. AI-Enabled Sustainability Value Creation: Mechanisms, Enabling Conditions, and Contingencies

A process-oriented understanding of AI-enabled sustainability value creation requires attention not only to outcomes but also to the mechanisms and conditions through which those outcomes are produced. Mechanisms refer here to the explanatory processes through which AI contributes to sustainability-related effects. In industrial settings, these mechanisms may include prediction, optimisation, decision support, monitoring, coordination, adaptation, and automation, depending on the nature of the application and the level of analysis involved [1,2,8]. Focusing on mechanisms shifts attention from the mere presence of AI to how AI functions are translated into operational or strategic interventions that generate sustainability value.

The effects of AI depend on antecedent conditions that enable its meaningful deployment. These antecedents may include data availability, sensor integration, digital infrastructure, simulation capabilities, and interoperability, as well as organisational factors such as dynamic capabilities, resource orchestration, managerial support, sustainability orientation, and strategic alignment [6,8,10]. In other words, AI-enabled sustainability value creation depends not only on technical readiness but also on the organisational capacity to combine, align, and mobilise resources in support of sustainability-oriented goals [10,11].

Finally, the relationship between AI and sustainability outcomes is shaped by contingency factors. These may include regulatory pressure, market dynamism, industrial sector characteristics, organisational size, technological maturity, and broader ecosystem conditions [6,7,15]. Such contingencies help explain why similar AI applications may produce different forms or levels of sustainability value across contexts. Mechanisms, antecedent conditions, and contingency factors show that AI-enabled sustainability value creation is a contingent, multi-stage, and organisationally embedded process rather than a direct technological effect [8,10,15].

These conceptual elements provide the analytical logic of the review. They suggest that AI-enabled sustainability value creation in industrial systems should be examined not only in terms of application domains, but also in relation to the types of sustainability value reported, the mechanisms through which value is generated, the antecedent conditions that enable those mechanisms, and the contingency factors that shape their effectiveness. This conceptual framing provides the basis for the review methodology and for the structured interpretation developed later in the article.

3. Materials and Methods

3.1. Research Design

This study adopts a systematic literature review (SLR) to identify, analyse, and synthesise the scientific literature on the relationship between AI and sustainability value creation in industrial systems. An SLR is particularly appropriate given the fragmented, interdisciplinary, and still-emerging nature of this topic, which spans digital transformation, industrial management, sustainability, information systems, and operations management [15]. The review provides a structured synthesis of the field and supports the identification of conceptual gaps, recurring explanatory patterns, and directions for future research.

The review was conducted according to the principles of transparency, rigour, and replicability, following a methodological logic informed by PRISMA 2020 [17]. The purpose of the review was not merely to catalogue AI applications in industrial settings, but to develop a conceptually oriented synthesis of the mechanisms of value creation, the sustainability dimensions addressed, and the organisational and contextual conditions shaping the relationship between AI and sustainability outcomes in industrial systems.

An a priori review protocol was registered on the Open Science Framework (OSF; <https://doi.org/10.17605/OSF.IO/FBAEY>), thereby enhancing the transparency and traceability of the review process in line with current systematic review recommendations. The protocol specified the main research question, secondary research questions, inclusion and exclusion criteria, selected databases, screening procedures, the involvement of two independent reviewers, and the assessment of inter-rater agreement through Cohen's kappa [18].

Consistent with the capability- and process-oriented perspective adopted in Section 2, the review was designed not only to identify where AI is applied in industrial sustainability contexts, but also to examine how AI-enabled sustainability value creation is explained across different levels of industrial analysis, including process, plant, firm, supply-chain, and ecosystem contexts. Particular attention was devoted to recurring explanatory mechanisms, enabling antecedent conditions, contextual contingencies, and persistent conceptual gaps in the literature.

3.2. Search Strategy

The search strategy was developed in accordance with the PRISMA 2020 guidelines for systematic literature reviews [17] and followed established recommendations for designing transparent and reproducible review protocols [19]. The strategy was conceptually derived from the review objective and structured around the three core dimensions required to identify studies simultaneously addressing artificial intelligence, sustainability, and industrial systems. This conceptual structure ensured close alignment between the review question and the evidence retrieved.

Three multidisciplinary bibliographic databases—Scopus, Web of Science, and IEEE Xplore—were selected because they collectively provide broad coverage of engineering, manufacturing, information systems, operations management, sustainability, and industrial digital transformation research. Their complementary disciplinary coverage reduces the likelihood of database-specific bias while ensuring representation of both technical and managerial perspectives.

The search covered publications published between 2020 and 2025, a period characterised by the rapid expansion of industrial AI applications and growing interest in sustainable manufacturing and digital transformation.

The search string was constructed by combining keywords representing the three conceptual domains underpinning the review: (i) Artificial Intelligence (e.g., artificial intelligence, machine learning, deep learning); (ii) Sustainability (e.g., sustainability, sustainable manufacturing, energy efficiency, resource efficiency, decarbonisation, circular economy); and (iii) Industrial Context (e.g., manufacturing, industrial systems, production systems, smart manufacturing). These terms were combined using Boolean operators and applied to titles, abstracts, and author keywords. Minor syntax adaptations were introduced where necessary to accommodate the indexing requirements of each database while preserving conceptual equivalence across searches.

The strategy intentionally focused on studies in which artificial intelligence, sustainability, and the industrial context constituted the central analytical themes. Consequently, publications addressing AI without substantive sustainability implications or sustainability

studies lacking an explicit AI component were not expected to satisfy the inclusion criteria. This approach was consistent with the objective of explaining the mechanisms through which AI contributes to sustainability value creation in industrial systems, rather than producing a broad review of digital transformation technologies.

3.3. Eligibility Criteria

The eligibility criteria were established a priori to ensure that the final analytical corpus remained closely aligned with the review objective of examining AI-enabled sustainability value creation in industrial systems.

Studies were considered eligible if they: (i) examined the application of artificial intelligence techniques within industrial or manufacturing environments; (ii) explicitly addressed one or more sustainability-related outcomes (e.g., environmental, economic, or operational sustainability); and (iii) provided sufficient methodological and conceptual information to support qualitative analysis and data extraction.

Studies were excluded if they: (i) focused exclusively on algorithm development or technical model performance without discussing sustainability implications; (ii) addressed sustainability without an explicit artificial intelligence component; (iii) examined non-industrial application contexts; or (iv) lacked sufficient information to determine their relevance to the review objective.

The eligibility criteria were applied consistently throughout the title and abstract screening stage and subsequently confirmed during the full-text assessment to ensure conceptual consistency across the final analytical corpus.

3.4. Study Selection Process

The study selection process followed a multi-stage procedure combining database screening, computational relevance assessment, and manual reviewer evaluation. This approach was designed to enhance transparency, consistency, and traceability while preserving expert judgement as the basis for all screening, eligibility, and analytical decisions. An overview of the complete study selection workflow is presented in Table 1, while the corresponding PRISMA flow diagram is shown in Figure 1.

Table 1. Summary of the study selection workflow combining computational relevance assessment and manual reviewer validation.

Stage	Procedure	Records (n)	Outcome
Database retrieval	Records identified in Scopus, Web of Science, and IEEE Xplore	2460	Initial corpus
Duplicate removal	Zotero duplicate detection	1563	Unique records
Document filtering	Removal of non-eligible publication types	1423	Records for computational assessment
Computational relevance assessment	Computational relevance assessment (Python 3.13 pipeline)	209 HR + 205 PR + 1149 Out of Scope	414 prioritised for manual screening
Manual screening	Title and abstract assessment	414	209 retained for full-text review
Full-text assessment	Eligibility assessment	209	75 included

The initial database search retrieved 2460 records, comprising 1291 from Scopus, 943 from Web of Science, and 226 from IEEE Xplore. Following duplicate removal using Zotero, 1563 unique records remained. A further 140 records were excluded because they did not meet the predefined document type criteria (primarily conference papers, edito-

rials, technical notes, and other non-eligible publication types), resulting in 1423 records submitted to the computational relevance assessment stage.

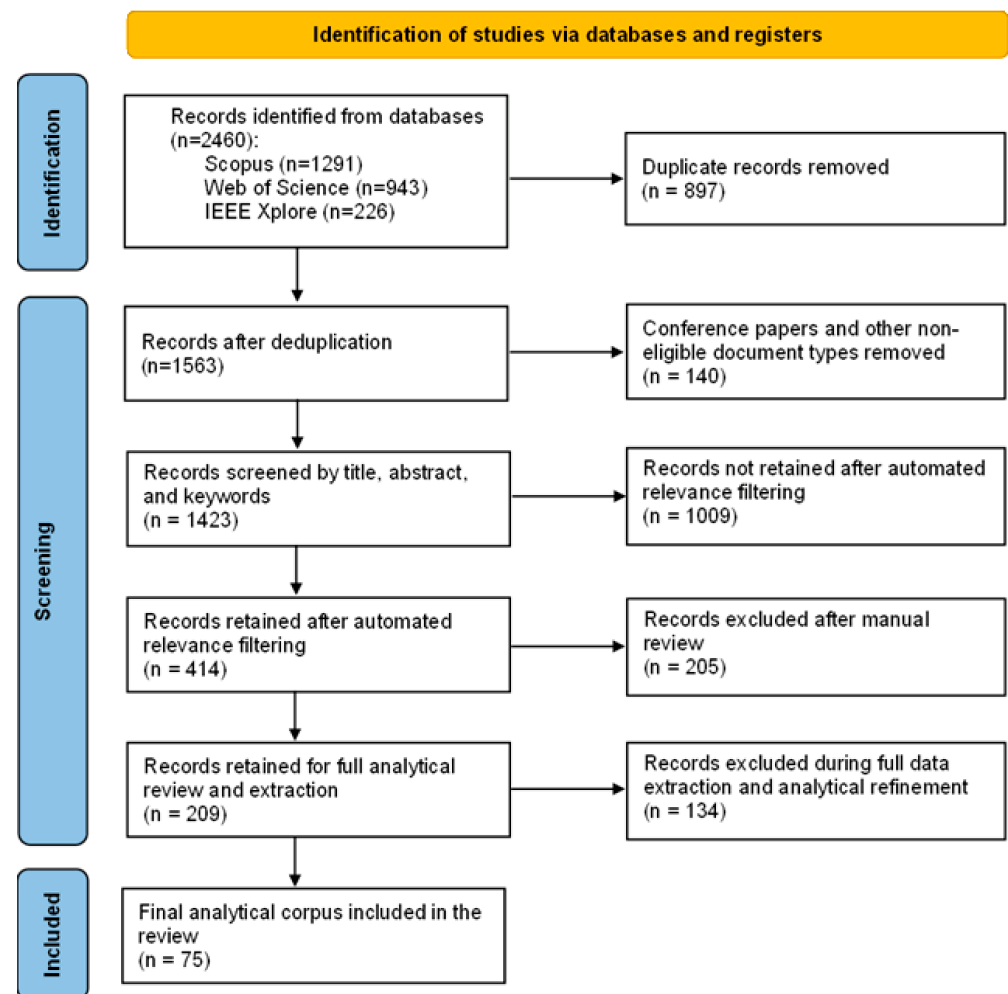


Figure 1. PRISMA 2020 flow diagram of the study selection process.

To support the screening of this large interdisciplinary corpus, a Python 3.13 computational relevance assessment pipeline was developed using pandas, regex (re), unicode, and spaCy (Python 3.13). The pipeline incorporated three domain-specific keyword dictionaries representing the core conceptual dimensions of the review: artificial intelligence, sustainability, and industrial/manufacturing context. Rather than serving as an automated selection mechanism, the algorithm functioned as a prioritisation tool to support reviewer decision-making. Titles, abstracts, and author keywords were analysed against these keyword dictionaries, and weighted scoring rules were applied to generate an overall relevance score for each record. Based on predefined decision rules, records were classified into four relevance categories: Highly Relevant (n = 209), Potentially Relevant (n = 205), Low Relevance, and Likely Out of Scope (n = 1149).

The complete computational workflow, including the Python 3.13 scripts, keyword dictionaries, weighted relevance scoring procedure, and analytical codebook, is provided in the Supplementary Materials to facilitate transparency, reproducibility, and methodological verification.

All records classified as Highly Relevant and Potentially Relevant (n = 414) were subsequently subjected to manual title and abstract screening. During this stage, each record was independently assessed by two reviewers against the predefined eligibility criteria. To evaluate the consistency of the screening process, a stratified random sample

representing approximately 10% of the screened records ($n = 156$) was independently assessed using a three-level relevance scale. Inter-rater agreement reached Cohen's $\kappa = 0.91$, indicating almost perfect agreement according to the interpretation proposed by Landis and Koch [18], thereby supporting the reliability and consistency of the screening procedure.

Following title and abstract screening, 209 studies were retained for full-text assessment. A structured pre-extraction script was then used to generate analytical tables supporting the organisation of study characteristics, preliminary thematic grouping, and preparation for manual coding. This computational support facilitated analytical consistency but did not perform automated coding or influence eligibility decisions. All thematic coding, interpretation, and framework development remained fully reviewer-driven and were validated through consensus.

During the full-text assessment, 205 studies were excluded because they did not demonstrate sufficient conceptual alignment with the review objective, while a further 134 studies were excluded because they did not provide sufficient empirical or conceptual evidence to support the explanation of AI-enabled sustainability value creation mechanisms. The remaining 75 peer-reviewed studies constituted the final analytical corpus.

Figure 1 presents the PRISMA 2020 flow diagram of the study selection process. Together with Table 1, it illustrates the sequential workflow from database retrieval to the final analytical corpus, distinguishing computational relevance assessment from reviewer-driven screening, full-text eligibility assessment, and analytical coding procedures, thereby enhancing methodological transparency and reproducibility.

3.5. Data Extraction and Analysis

Following full-text eligibility assessment, the final analytical corpus comprising 75 studies underwent structured data extraction using a review-specific analytical codebook. The extraction grid captured bibliographic information (authors, publication year, journal, and geographical context), study characteristics (industrial sector, research methodology, and empirical setting), AI technologies, application domains, sustainability dimensions, value creation mechanisms, antecedent organisational conditions, contextual contingencies, principal findings, and research gaps identified by the original authors. The complete analytical codebook is provided in Supplementary File S4.

The analytical process comprised three complementary stages. First, a descriptive analysis was performed to characterise the temporal evolution of publications, the industrial contexts investigated, the research methods employed, and the principal AI application domains reported in the literature. Second, a thematic analysis was conducted to identify recurring patterns related to sustainability value types, AI-enabled mechanisms, antecedent organisational conditions, contextual contingencies, and emerging research gaps, following the principles of thematic analysis proposed by Braun and Clarke [20]. Third, a concept-centred synthesis was undertaken to integrate the extracted evidence and develop a coherent explanation of how AI-enabled sustainability value creation has been conceptualised across industrial systems, consistent with the approach recommended by Webster and Watson [21].

Computational support was used exclusively to facilitate the organisation and preliminary structuring of the extracted information. A pre-extraction pipeline generated analytical support tables that assisted reviewer navigation across the corpus but did not perform automated coding or determine study classifications. All analytical coding, interpretation, and framework development remained reviewer-driven. Coding followed the principle of analytical parsimony, whereby each study was assigned a single dominant code for each core analytical category whenever possible. For studies addressing multiple mechanisms, application domains, or sustainability outcomes, classification prioritised

the dimension representing the study's principal theoretical or empirical contribution. Borderline cases and ambiguous classifications were resolved through iterative discussion between the reviewers until consensus was achieved. Detailed descriptions of the computational workflow, coding procedures, and analytical codebook are provided in Supplementary Files S2–S4.

This analytical strategy was designed to ensure direct alignment between the review methodology and the research questions while moving beyond descriptive mapping towards an explanatory understanding of how AI-enabled sustainability value creation emerges, is conditioned, and is sustained across industrial systems.

3.6. Analytical Framework for Evidence Synthesis

Rather than providing a descriptive inventory of AI applications in industrial settings, this review adopted a mechanism-oriented analytical perspective centred on sustainability value creation. Accordingly, the synthesis of the evidence was organised around five complementary analytical axes: (i) AI application domains in industrial systems; (ii) sustainability value outcomes; (iii) AI-enabled value creation mechanisms; (iv) organisational, technological, and contextual conditions influencing sustainability value creation; and (v) persistent conceptual and research gaps identified across the literature.

These five analytical axes operationalise the review questions and provide the analytical structure through which the evidence is synthesised in Section 4. Their integration enabled the development of the mechanism-based framework proposed in this study by identifying recurring relationships between antecedent organisational conditions, AI-enabled mechanisms, industrial application domains, sustainability outcomes, and contextual contingencies. Consequently, the framework represents an interpretative synthesis derived from the collective evidence of the reviewed studies rather than a simple descriptive classification of the existing literature.

4. Results

This section presents the results of the review in line with the study's analytical orientation and research questions. It begins with a descriptive overview of the final corpus and then examines the findings across the five analytical dimensions guiding the review.

4.1. Descriptive Overview of the Final Corpus

The final analytical corpus comprised 75 peer-reviewed journal articles published between 2020 and 2025. The descriptive profile of the corpus indicates that AI-enabled sustainability value creation in industrial systems remains an emerging and rapidly expanding research field characterised by a strong techno-operational orientation, a concentration at lower levels of industrial analysis, and comparatively limited development of broader organisational and systemic sustainability perspectives.

4.1.1. Publication Evolution

The temporal distribution of the corpus indicates a marked acceleration of publications during the most recent years of the review period. More than half of the studies included in the final corpus, specifically 54%, were published between 2024 and 2025, reflecting the recent intensification of industrial AI adoption together with growing sustainability and decarbonisation pressures across manufacturing and industrial sectors. This recent growth is illustrated by studies on AI-enabled energy optimisation, sustainable process control, and industrial efficiency published in 2024–2025, including work on plant-level energy optimisation, sustainable manufacturing analytics, and smart process improvement [22–29].

This rapid publication growth suggests that AI-enabled sustainability value creation remains a relatively recent and still consolidating research stream rather than a mature and

theoretically stabilised field. The accelerated expansion of the literature also helps explain the coexistence of heterogeneous terminologies, fragmented analytical approaches, and uneven conceptual development across the corpus.

4.1.2. Methodological Profile of the Literature

The corpus is strongly dominated by technical and model-development-oriented studies. Of the 75 analysed articles, 54 studies (72%) were classified as primarily technical, simulation-based, optimisation-oriented, or model-development contributions, while 11 studies (15%) adopted empirical quantitative approaches, three studies (4%) employed qualitative methodologies, one study (1%) used a mixed-methods design, and six studies (8%) corresponded to conceptual or model-oriented contributions. This distribution is consistent with a field in which many contributions focus on optimisation architectures, predictive models, digital twins, and process-control solutions, such as studies on boiler efficiency optimisation, semiconductor plant energy management, injection-moulding optimisation, and AI-supported waste reduction [23,30–36].

This methodological distribution reflects the strong concentration of the field around optimisation-oriented industrial applications.

4.1.3. Levels of Analysis

The literature is also highly concentrated at operational and process-oriented levels of analysis. Twenty-eight studies (37%) focused primarily on plant- or facility-level applications, while 24 studies (32%) examined process-level industrial optimisation problems. In comparison, only 10 studies (13%) adopted firm-level perspectives, seven studies (9%) addressed supply-chain contexts, and four studies (5%) examined industry- or ecosystem-level sustainability dynamics.

This concentration at lower analytical levels is significant because it helps explain why much of the literature privileges operational efficiency and local optimisation outcomes over broader organisational, systemic, and transformational sustainability perspectives. Process- and plant-level studies frequently focus on measurable improvements in energy consumption, emissions reduction, machine performance, scheduling optimisation, and production control, whereas higher-level organisational and inter-organisational sustainability dynamics remain comparatively underdeveloped, as illustrated by the contrast between operational studies in plants and broader firm- or ecosystem-level studies on orchestration, circularity, sustainability capabilities, and AI-enabled industrial transformation [6,8,25,37,38].

4.1.4. Dominant Publication and Analytical Patterns

Across the corpus, AI-enabled sustainability value is most frequently associated with operational efficiency, energy optimisation, emissions reduction, predictive maintenance, process optimisation, and intelligent production management. The dominant AI-related approaches include machine learning, deep learning, optimisation algorithms, reinforcement learning, and predictive analytics integrated within Industry 4.0 and smart manufacturing environments. This pattern is visible in studies on energy forecasting in manufacturing firms, reinforcement-learning-based scheduling, machining optimisation, heating, ventilation, and air conditioning (HVAC) efficiency modelling, and predictive planning in energy-intensive industries [39–44].

However, fewer studies explicitly examine broader sustainability dimensions such as organisational resilience, circularity, governance, capability development, sustainability-oriented coordination, or long-term sustainability transformation processes. Similarly, social and governance-related sustainability dimensions remain considerably less visible across the final corpus than environmental and operational outcomes (Table 2).

Table 2. Analytical profile of the final corpus (n = 75).

Dimension	Main Pattern	Evidence
Publication period	Strong recent growth	54% published in 2024–2025
Methodological orientation	Predominance of technical/model-development studies	54 of 75 studies (72%)
Levels of analysis	Concentration at process and plant levels	52 of 75 studies (69%)
Sustainability focus	Dominance of environmental and operational outcomes	Frequent focus on energy, efficiency, and emissions
Organisational perspectives	Limited development of organisational explanations	Few studies address capabilities or orchestration
Broader sustainability dimensions	Comparatively underdeveloped	Limited focus on resilience, governance, or circularity

4.2. Main AI Application Domains in Industrial Sustainability

This section addresses RQ1 by examining the principal application domains through which AI has been associated with sustainability value creation in industrial systems. Beyond identifying where AI is applied, the analysis also examines what the distribution of application domains reveals about how sustainability itself is conceptualised within the literature.

The identification of application domains followed an iterative coding process combining preliminary computational tagging with subsequent manual refinement and reviewer validation. Studies were assigned to one or more domains according to their primary industrial AI application and dominant sustainability problem orientation, and coding disagreements were resolved through reviewer discussion and consensus, particularly in studies where sustainability outcomes overlapped across energy management, process optimisation, and production-control contexts.

Overall, the literature is strongly concentrated around operational and efficiency-oriented industrial sustainability problems. The dominant application domains identified across the corpus include energy management, process optimisation, predictive maintenance, quality control, production scheduling, emissions reduction, waste management, circular manufacturing, facility management, and sustainable supply-chain management. However, energy management and process optimisation clearly dominate the field.

Energy management emerged as the most prominent application domain across the final corpus. A substantial proportion of studies examined how AI techniques such as machine learning, reinforcement learning, predictive analytics, and digital twins contribute to reducing industrial energy consumption, improving energy forecasting, optimising machine states, reducing peak demand, and improving operational energy efficiency. Illustrative examples include studies on large-scale plant energy optimisation, semiconductor-facility energy modelling, manufacturing energy forecasting, job-shop scheduling and energy estimation, and process-firm energy improvement [25,29,42,45–51]. In these studies, sustainability is predominantly framed through operational efficiency and environmental optimisation logics, with AI functioning primarily as a predictive and optimisation-oriented infrastructure supporting energy-related decision-making processes.

Process optimisation constituted the second dominant application domain. These studies typically examined AI-enabled optimisation of machining processes, combustion systems, additive manufacturing, scheduling systems, injection moulding, production control, and process parameter tuning. Sustainability outcomes were generally associated with reduced material waste, lower energy use, improved process efficiency, reduced emissions,

and enhanced production quality. This is evident in studies on boiler combustion optimisation, CNC machining, sustainable turning operations, injection-moulding parameter optimisation, cutting-fluid optimisation, and furnace process modelling [23,35,43,52–60].

Other application domains appeared less consistently across the corpus. Predictive maintenance studies frequently associated AI with machine reliability, equipment lifespan extension, and operational continuity, as in work on Industry 4.0 maintenance planning and energy-based maintenance solutions [61–63]. Supply-chain and logistics-oriented studies examined sustainable coordination, visibility, decarbonisation, and supplier selection across broader inter-organisational contexts, including AI-driven green supply chains, digital-circular synergies, and green supplier evaluation [13,36,64–66]. Circular manufacturing studies addressed material reuse, waste reduction, and circular production systems, although these remained comparatively limited in number, as shown in studies on carbon fibre manufacturing, circular manufacturing capability, and recycling-oriented inspection systems [1,8,34,67] (Table 3).

Table 3. Dominant AI application domains and sustainability value orientations.

Application Domain	Main Sustainability Focus	Dominant AI Mechanisms
Energy management	Energy efficiency and emissions reduction	Prediction, optimisation, adaptive control
Process optimisation	Operational efficiency and waste reduction	Optimisation, monitoring, anomaly detection
Predictive maintenance	Resource efficiency and operational continuity	Prediction, anomaly detection
Supply-chain management	Coordination and logistics sustainability	Decision support, forecasting
Circular manufacturing	Material reuse and waste minimisation	Classification, optimisation
Quality control	Resource savings and process efficiency	Monitoring, anomaly detection

The distribution of application domains reveals a broader interpretive pattern within the literature. The predominance of energy management and process optimisation indicates that AI-enabled sustainability value creation is still largely conceptualised through local operational optimisation problems rather than through broader organisational or systemic sustainability transformation processes. In most studies, sustainability outcomes are closely associated with measurable efficiency gains at the process or facility level, whereas comparatively few contributions examine how AI supports resilience, governance, capability development, circular coordination, or long-term sustainability transformation across industrial ecosystems [8,47]. This contrast can be seen between highly operational studies and the smaller set of firm- and ecosystem-level contributions examining resource orchestration, circularity, or strategic sustainability performance [6,14,68].

4.3. Types of Sustainability Value Reported

This section addresses RQ2 by examining the dominant types of sustainability value reported across the literature and by analysing how sustainability itself has been conceptualised within AI-enabled industrial contexts.

Overall, the literature reveals a strong concentration around environmental and economic-operational forms of sustainability value. Across the corpus, sustainability outcomes are most frequently associated with operational efficiency, energy efficiency, emissions reduction, resource optimisation, waste reduction, cost savings, and process-performance improvement. In contrast, broader social, governance, resilience-oriented, and transformational sustainability dimensions remain comparatively underdeveloped.

Table 4 summarises the frequency of the sustainability outcomes identified across the analytical corpus, providing a quantitative overview of the dominant forms of value reported in the literature.

Table 4. Distribution of AI-enabled sustainability outcomes across the reviewed studies.

Sustainability Outcome	Frequency (n)
Operational efficiency	47
Energy efficiency	41
Resource efficiency	20
Emissions reduction	16
Cost reduction	15
Sustainable performance	13
Quality improvement	12
Waste reduction	11
Environmental performance	7
Decarbonization	5
Circularity improvement	3
Resilience/adaptability	1
Material reuse	1
Green productivity	1

Note. Because individual studies may report multiple sustainability outcomes, frequencies are not mutually exclusive, and totals exceed the number of included studies (n = 75).

As shown in Table 4, operational efficiency (n = 47) and energy efficiency (n = 41) are by far the most frequently reported sustainability outcomes, followed by resource efficiency (n = 20), emissions reduction (n = 16), and cost reduction (n = 15). This distribution confirms that the current literature remains predominantly oriented towards measurable operational and environmental improvements achieved through process optimisation rather than towards broader organisational or systemic sustainability objectives.

A substantial proportion of studies associated AI-enabled sustainability improvements with reduced energy consumption, lower peak demand, improved machine utilisation, process optimisation, and increased production efficiency. In these studies, sustainability value is frequently operationalised through measurable efficiency indicators and environmental performance metrics closely linked to industrial optimisation processes. This pattern is illustrated by studies on semiconductor plants, large-scale industrial plants, sustainable textile dyeing, smart manufacturing scheduling, and manufacturing-system idle-time prediction [41,47,51,69–73].

Environmental outcomes also appear prominently across the literature, particularly through emissions reduction, carbon optimisation, cleaner production systems, and decarbonisation-oriented industrial interventions. AI-enabled forecasting, optimisation, and monitoring systems are commonly associated with reductions in resource consumption, carbon emissions, and environmental impact intensity. Examples include studies on industrial robots and carbon emissions reduction, AI-enabled decarbonisation, laser-based emissions optimisation, sustainable leather cutting, and green supply-chain carbon reduction [36,60,74–76].

Economic and operational value dimensions frequently appear intertwined with environmental sustainability outcomes. Many studies present sustainability value through the simultaneous achievement of lower operational costs, increased productivity, reduced

waste, improved throughput, and enhanced production efficiency. This dual environmental-economic framing reinforces the predominantly techno-operational orientation of the literature, where sustainability is often interpreted through the lens of industrial optimisation and measurable performance gains [44,77].

In contrast, broader sustainability dimensions remain comparatively less visible across the corpus. Only a smaller subset of studies explicitly addresses sustainability value through concepts such as organisational resilience, circularity, adaptive capability development, sustainable supply-chain coordination, governance improvement, or long-term sustainability transformation. These broader perspectives are more visible in studies on sustainable performance through green supply-chain practices, circular manufacturing and dynamic capabilities, digital-circular synergies, and Industry 5.0–circular economy complementarities [8,24,37,64,66,78]. Social sustainability dimensions, including workforce implications, organisational learning, employee wellbeing, or governance-related sustainability processes, are particularly underrepresented within the final corpus.

The literature also reveals a distinction between proximal sustainability outcomes and broader sustainability value creation. Most studies provide evidence of proximal operational gains, including energy optimisation, emissions reduction, process efficiency, and waste minimisation. However, comparatively few studies explain how these local operational improvements are translated into broader organisational or systemic sustainability outcomes across firms, supply chains, or industrial ecosystems. This limitation is visible in the contrast between highly operational studies and the smaller set of explanatory studies centred on orchestration, resilience, and multilevel sustainability performance [8,22,47,79].

While the previous section examined the sustainability outcomes reported in the literature, the following analysis shifts attention to the underlying mechanisms through which AI contributes to those outcomes.

4.4. AI-Enabled Mechanisms of Sustainability Value Creation

This section addresses RQ3 by examining the principal mechanisms through which AI-enabled sustainability value creation is explained across the literature. Rather than focusing exclusively on AI applications or sustainability outcomes, the analysis here explores how studies conceptualise the processes linking AI functionalities to sustainability-related industrial improvements.

Across the final corpus, the literature consistently associates AI-enabled sustainability value creation with a relatively concentrated set of recurring mechanisms. The most dominant mechanisms identified include prediction, optimisation, monitoring, adaptive control, automation, anomaly detection, and decision support [23,45,80–82]. These mechanisms frequently operate as intermediate processes through which AI functionalities become translated into operational sustainability outcomes.

Table 5 summarises the frequency of the AI-enabled mechanisms identified across the reviewed studies, providing an overview of the dominant explanatory processes through which AI contributes to sustainability value creation.

As shown in Table 5, decision support emerged as the most frequently identified AI-enabled mechanism ($n = 56$), followed by prediction ($n = 40$) and optimisation ($n = 35$). Together, these mechanisms indicate that AI contributes to sustainability primarily by supporting managerial and operational decision-making, improving forecasting capabilities, and optimising industrial processes. By contrast, mechanisms such as automation, control, and resource orchestration appear comparatively infrequently, suggesting that the literature continues to emphasise analytical support over fully autonomous sustainability-oriented industrial systems.

Table 5. Distribution of AI-enabled value creation mechanisms identified in the reviewed studies.

AI-Enabled Mechanism	Frequency (n)
Decision support	56
Prediction	40
Optimisation	35
Monitoring/visibility	22
Capability development	18
Coordination	10
Classification/detection	7
Control	6
Automation	5
Resource orchestration	1

Note. Frequencies reflect the occurrence of each mechanism across the analytical corpus. Individual studies may contribute to more than one mechanism.

Numerous studies examined how AI-based predictive models contribute to energy forecasting, predictive maintenance, demand estimation, process stability, and equipment reliability improvements. In these contexts, AI-enabled prediction mechanisms are primarily associated with reducing operational uncertainty, improving planning accuracy, preventing equipment failures, and supporting more efficient resource utilisation. Representative examples include studies on idle-duration prediction, power-consumption prediction, production planning, machining-power prediction, and loss prediction in industrial production systems [46,51,56,62,72,83].

Optimisation mechanisms also appeared prominently throughout the literature. AI-driven optimisation systems are frequently used to improve production scheduling, minimise energy consumption, optimise process parameters, reduce material waste, and improve operational throughput. Sustainability value in these studies is generally generated through incremental improvements in process efficiency, operational precision, and resource allocation. This is illustrated by studies on reinforcement-learning scheduling, boiler combustion control, injection-moulding optimisation, milling-energy optimisation, and cutting-fluid optimisation [23,35,41,54,57,77,84].

Monitoring and adaptive control mechanisms represent another important category identified across the corpus. Several studies examined how AI-supported monitoring systems enable real-time process supervision, anomaly detection, dynamic operational adjustment, and intelligent system coordination. These mechanisms are particularly relevant in Industry 4.0 and smart manufacturing environments characterised by sensor networks, IoT integration, and continuous industrial data generation. Examples include AI-based defect detection, plant monitoring, HVAC supervision, and monitoring-driven energy optimisation in smart manufacturing contexts [39,42,44,53,69,85].

Decision-support mechanisms also appear frequently in studies examining sustainability-oriented industrial coordination and managerial decision-making processes. In these cases, AI contributes by supporting scenario analysis, operational planning, sustainability-oriented optimisation choices, and complex system coordination. However, decision-support mechanisms remain more strongly represented at operational decision levels than at strategic or organisational sustainability governance levels. This is evident in studies on energy-management decision support, green supplier selection, sustainable firm performance, and smart industrial analytics [8,24,29,37,65,85].

The analysis also reveals that most AI-enabled mechanisms identified across the literature remain strongly techno-operational in orientation. Comparatively few studies conceptualise sustainability value creation through broader organisational processes such as capability development, sustainability-oriented orchestration, inter-organisational coordination, or organisational learning. These more organisation-centred mechanisms appear mainly in studies on resource orchestration, sustainable innovation ambidexterity, circular manufacturing, and green supply-chain practices [6,7,22,66,86].

Taken together, these findings suggest that AI-enabled sustainability value creation depends not only on technical mechanisms themselves, but also on the organisational conditions through which such mechanisms become embedded and coordinated across industrial contexts.

4.5. Enabling Conditions and Contextual Contingencies

This section addresses the third research question by examining the enabling organisational and technological conditions together with the contextual contingencies shaping AI-enabled sustainability value creation across industrial systems. The findings show that sustainability value creation does not emerge uniformly across industrial contexts but is instead strongly conditioned by organisational readiness, technological infrastructure, industrial characteristics, and broader contextual dynamics [14,24,85].

Across the final corpus, digital infrastructure and data-related capabilities emerged as the most recurrent enabling conditions. Many studies emphasised the importance of sensor integration, IoT connectivity, interoperable systems, cloud infrastructures, real-time monitoring architectures, and high-quality industrial datasets as foundational requirements for effective AI deployment in sustainability-oriented industrial environments. This is visible in studies on IIoT adoption, semiconductor energy monitoring, HVAC optimisation, and digitalised decision-support implementation [25,42,69,80,82,85].

Technological maturity and Industry 4.0 integration also appear as important enabling conditions across the literature. Several studies indicate that AI-enabled sustainability value creation is significantly facilitated by broader digital transformation environments characterised by cyber-physical systems, smart manufacturing architectures, automation infrastructures, and advanced industrial connectivity. AI rarely operates as an isolated technological intervention and is instead frequently embedded within wider industrial digitalisation trajectories. Illustrative examples include studies on digital twins, smart manufacturing optimisation, semiconductor sustainability, and Industry 4.0 implementation [38,39,41,85].

At the organisational level, the literature highlights the importance of managerial support, organisational readiness, sustainability-oriented strategic alignment, and implementation capability. Studies addressing broader organisational sustainability perspectives indicate that AI-enabled sustainability outcomes depend not only on technical deployment but also on the ability of organisations to align AI adoption with sustainability priorities, operational coordination processes, and long-term transformation objectives. These themes are visible in studies on dynamic capabilities, resource orchestration, environmental sustainability, circular manufacturing, and sustainable innovation ambidexterity [6–8,22,37].

The findings also reveal the importance of contextual contingencies shaping AI-enabled sustainability outcomes. Industry characteristics, regulatory environments, organisational size, technological capability, market pressure, energy intensity, and supply-chain complexity frequently influence how AI-enabled sustainability interventions are implemented and interpreted across industrial systems. Regulatory and sustainability-related pressures appear particularly relevant in studies examining emissions reduction, industrial decarbonisation, energy optimisation, and environmental compliance processes. Exam-

ples include studies on manufacturing decarbonisation, industrial robots and emissions reduction, and sustainability transitions under different industrial conditions [75,86,87].

The findings suggest that sustainability outcomes depend on the interaction between AI capabilities, organisational conditions, and contextual factors across industrial settings.

4.6. Conceptual Gaps and Emerging Interpretive Patterns

The reviewed literature collectively provides substantial evidence regarding AI applications, operational sustainability improvements, and industrial optimisation mechanisms. However, important conceptual limitations remain in how AI-enabled sustainability value creation has been theoretically explained across industrial systems.

A first limitation concerns the predominance of techno-operational perspectives throughout the field. Most studies conceptualise sustainability value creation through direct relationships linking AI functionalities to operational improvements such as energy optimisation, emissions reduction, predictive maintenance, and production-efficiency gains. While these contributions provide important evidence regarding the operational potential of AI, they frequently interpret sustainability outcomes as relatively direct consequences of technological optimisation processes [23,88–90].

A smaller body of work examines how AI-enabled sustainability value creation depends on broader organisational, managerial, and institutional processes. Organisational coordination, sustainability-oriented governance, capability development, strategic alignment, and inter-organisational collaboration remain considerably less developed across the corpus. As a result, the literature is substantially stronger in explaining operational performance improvements than in clarifying how sustainability value becomes organisationally embedded and sustained over time. These broader perspectives appear mainly in studies addressing orchestration, circularity, sustainable performance, and capability-oriented approaches [8,24,37,66].

The literature also remains predominantly centred on proximal operational sustainability outcomes, while broader transformation-oriented perspectives remain comparatively less developed. Most studies focus on process-level efficiency improvements and environmental optimisation metrics, whereas resilience, circularity, governance, and long-term sustainability transformation receive comparatively less attention [64,66,78,86,87,91].

Another important limitation concerns the weak integration between AI-enabled mechanisms, enabling organisational conditions, and contextual contingencies. Although many studies acknowledge the relevance of factors such as digital infrastructure, Industry 4.0 maturity, managerial support, regulatory pressure, and sustainability-oriented strategy, these dimensions are rarely integrated into coherent explanatory perspectives capable of clarifying why similar AI applications may produce different sustainability outcomes across industrial contexts [14,36,80,82,92].

The findings suggest that the field remains fragmented not only thematically but also explanatorily. The literature provides substantial evidence regarding where AI is applied and which operational sustainability gains are achieved, yet fewer studies offer integrated explanations connecting AI-enabled mechanisms, organisational conditions, contextual contingencies, and multilevel sustainability outcomes across industrial systems.

5. Discussion

The findings of this review indicate that research on AI-enabled sustainability value creation in industrial systems remains strongly shaped by techno-operational perspectives, fragmented analytical structures, and comparatively limited integration between operational sustainability improvements and broader organisational transformation dynamics. Although the literature provides substantial evidence regarding AI applications,

optimisation mechanisms, and measurable sustainability-related gains, it is less developed in explaining how these gains become organisationally embedded, coordinated across analytical levels, and sustained over time. Overall, the review suggests that AI-enabled sustainability value creation should be understood not as a direct consequence of technological deployment alone, but rather as a contingent, multilevel, and organisationally embedded process shaped by implementation conditions, governance structures, and contextual contingencies.

5.1. Optimisation-Centric Sustainability and Multilevel Fragmentation

Across the reviewed literature, AI is most frequently associated with more visible and measurable forms of sustainability value creation, particularly energy efficiency, process optimisation, emissions reduction, predictive maintenance, and quality control. As shown in Tables 3 and 4, the reviewed studies are strongly concentrated on operational and environmental sustainability outcomes, which are primarily enabled through optimisation-, prediction-, and monitoring-oriented AI mechanisms. This pattern suggests that industrial AI research continues to privilege sustainability interventions that are measurable, immediate, and closely connected to production performance. Similar tendencies have been identified in recent reviews highlighting the predominance of optimisation-oriented and process-level sustainability applications within industrial AI research [5,14,93,94].

However, this optimisation-centric orientation also reveals an important conceptual imbalance. By concentrating primarily on proximal operational gains, the literature often underexplores the mechanisms through which local improvements become broader forms of sustainability value across firms, supply chains, and industrial ecosystems [22,24]. As a result, the field is substantially stronger at explaining how AI improves operational efficiency than at clarifying how such improvements contribute to resilience, circularity, long-term sustainability transformation, or strategic sustainability capability.

This imbalance is reinforced by the strong concentration of the literature at the process and plant levels. While many studies provide detailed accounts of technical interventions and their immediate effects on energy use, waste reduction, emissions control, and operational performance, comparatively few contributions examine how these interventions scale across organisational boundaries or generate system-level sustainability outcomes. Recent reviews on industrial AI and sustainability similarly conclude that the field remains rich in application-level evidence but comparatively weak at explaining cross-level sustainability transformation processes [8,14,28,58].

This multilevel fragmentation also helps explain why the present review required a multidimensional analytical perspective rather than a simpler descriptive mapping. Without distinguishing application domains, sustainability value dimensions, AI-enabled mechanisms, enabling conditions, and contextual contingencies, the literature would appear more coherent than it actually is. What emerges instead is a central tension within the field: AI is widely examined as a tool for industrial optimisation, but its role as an enabler of broader sustainability value creation remains unevenly theorised.

5.2. Mechanisms, Organisational Embedding, and Contextual Contingencies

The review identifies prediction, optimisation, monitoring, adaptive control, coordination, and decision support as the principal mechanisms linking AI to sustainability-related outcomes in industrial systems. This pattern is consistent with broader work on AI in industrial sustainability and management, which suggests that AI contributes most effectively when it supports actionable interventions rather than merely generating analytical insight [50,84,91,95].

However, the literature also indicates that these mechanisms should not be understood as self-sufficient technical functions. Similar predictive, optimisation, or monitoring routines may generate very different sustainability effects depending on how they are embedded within organisational structures, implementation processes, governance arrangements, and strategic priorities [78,79,92]. The central issue is therefore not only what AI does, but under which organisational and contextual conditions these mechanisms generate sustainability value [6,8,37].

This interpretive shift is important because the literature remains considerably stronger in identifying mechanisms than in explaining how those mechanisms operate across different industrial contexts. Many studies show that AI predicts, optimises, monitors, or supports decision-making, yet comparatively few clarify how such mechanisms are translated into broader and more durable forms of sustainability value [29,61,69]. The main analytical gap lies in explaining how technical capabilities become organisationally embedded sustainability capabilities.

The revised framework further suggests that AI-enabled mechanisms do not generate sustainability value directly. Rather, these mechanisms become effective only when they are embedded into operational transformation processes that reshape how industrial activities are organised, coordinated, and executed. Prediction, optimisation, and decision support contribute to sustainability value creation not through their technical functionality alone, but also through the operational changes they enable within production systems. This distinction helps explain why similar AI applications may generate substantially different sustainability outcomes across organisations operating under different organisational and contextual conditions.

The review also highlights the importance of enabling conditions and contextual contingencies in shaping these processes. Data infrastructure, digital maturity, interoperability, managerial support, strategic alignment, regulatory pressure, and sector-specific characteristics repeatedly appear as conditions that influence whether AI remains a local optimisation tool or evolves into a broader sustainability capability [28,69,82,92]. This view aligns with recent work on sustainable AI capabilities and organisational readiness, which emphasises that AI-related value creation depends on the interaction between technological deployment, organisational flexibility, and sustainability-oriented governance [68].

The framework was derived through a three-step synthesis process. First, descriptive coding identified dominant empirical categories across the corpus, including application domains, sustainability outcomes, methods, and levels of analysis. Second, interpretive coding grouped recurring explanatory elements into broader categories—antecedent conditions, mechanisms, application domains, outcomes, and contingencies. Third, concept-centred synthesis connected these categories into a process model showing how AI-enabled sustainability value creation moves from organisational and technological conditions to mechanisms, operational transformation processes, and sustainability outcomes under contextual contingencies.

Figure 2 synthesises this interpretation by conceptualising AI-enabled sustainability value creation as a dynamic organisational process. The framework illustrates how organisational antecedents enable AI-enabled mechanisms, which become embedded into operational transformation processes that generate immediate sustainability outcomes and, over time, broader sustainability value through organisational learning under different contextual contingencies.

The framework suggests that sustainability value does not emerge from AI deployment alone, but from the alignment between antecedent conditions, AI-enabled mechanisms, industrial application domains, and contextual fit. It also indicates that while operational sustainability gains may arise relatively directly through AI-supported mecha-

nisms, broader outcomes such as resilience, decarbonisation, supply-chain sustainability, and sustainability transformation depend more strongly on organisational coordination, strategic alignment, and the reinforcement of enabling conditions over time.

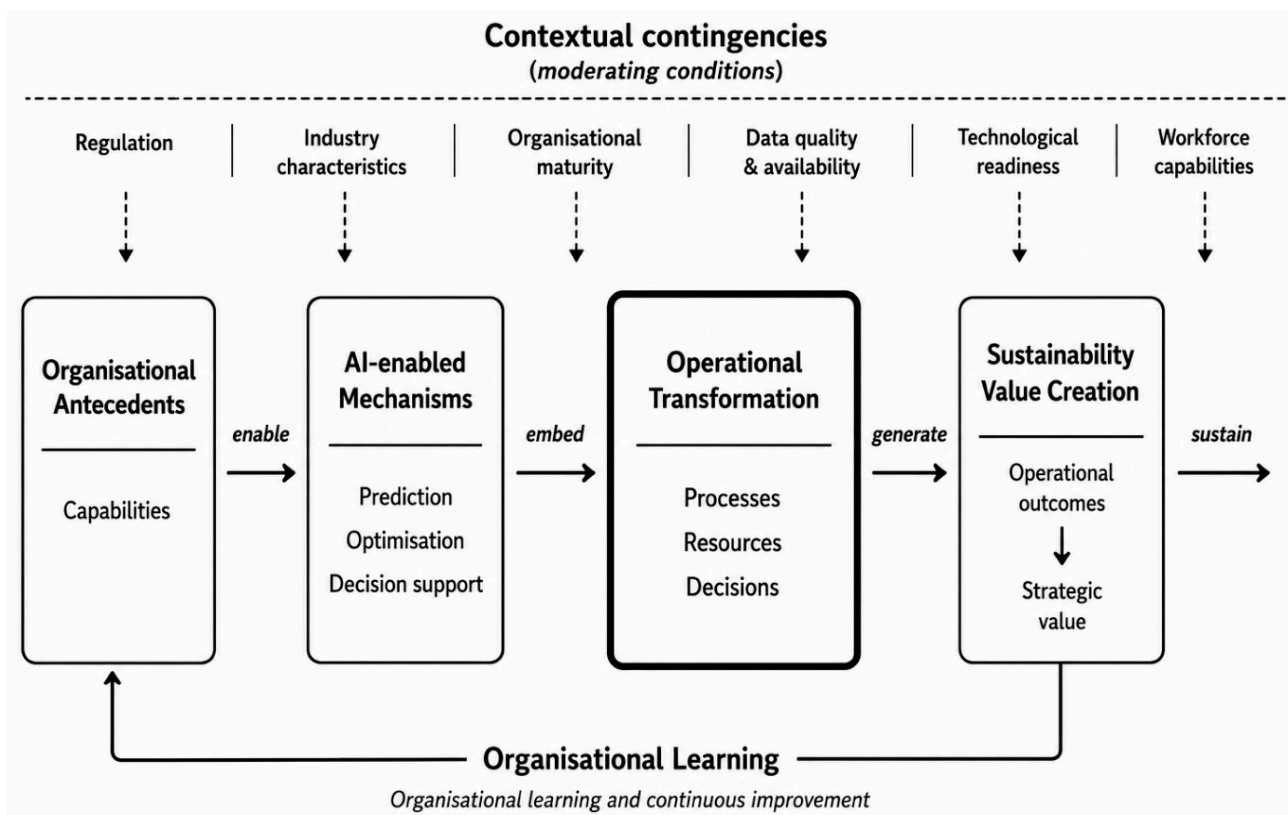


Figure 2. Mechanism-Based Framework of AI-Enabled Sustainability Value Creation.

The framework therefore shifts the analytical focus away from isolated AI applications and towards the processes through which sustainability value is generated, shaped, and sustained across industrial systems. In this way, it provides a more coherent explanation of why similar AI applications may produce uneven sustainability outcomes across different organisational and industrial contexts.

5.3. Theoretical Contributions

This review proposes a reframing of AI-enabled sustainability value creation as a contingent, multilevel, and organisationally embedded process—a perspective that the reviewed literature supports but has not yet systematically articulated. This shift is important because much of the existing literature still treats AI primarily as a technical instrument for operational optimisation, even when sustainability-related outcomes are discussed.

A first contribution lies in the integrative function of the framework. By connecting antecedent conditions, AI-enabled mechanisms, application domains, sustainability outcomes, and contextual contingencies, the framework brings together explanatory elements that are often treated separately [8,10,24,92]. In doing so, it provides a more coherent conceptual structure for understanding how AI contributes to sustainability value creation across industrial systems.

A second contribution concerns process-based, mechanism-oriented explanations. Rather than treating prediction, optimisation, monitoring, adaptive control, and decision support as isolated technical functions, the review conceptualises them as organisationally mediated mechanisms whose sustainability implications depend on implementation logic, strategic alignment, data integration, and contextual fit. This perspective strengthens

theoretical understanding by showing that similar AI functionalities may generate different outcomes depending on how they are embedded within industrial systems [22,68,96].

A third contribution concerns the distinction between proximal operational sustainability gains and broader forms of sustainability value creation. The review shows that operational improvements, such as efficiency gains, emissions reductions, process optimisation, and waste minimisation, are important but do not automatically translate into broader outcomes, such as resilience, circularity, long-term sustainability transformation, or supply-chain sustainability integration. This distinction helps explain why similar AI applications may produce uneven sustainability outcomes across industrial contexts and highlights the need to conceptualise sustainability value beyond immediate operational performance indicators [12,66,67,87].

Overall, the review contributes to a more integrated and theoretically grounded understanding of AI-enabled sustainability value creation by showing how AI-enabled mechanisms, organisational conditions, and contextual contingencies jointly shape multilevel sustainability outcomes across industrial systems.

5.4. Practical Implications

The findings suggest that industrial organisations should avoid treating AI as a standalone optimisation tool. Instead, AI initiatives should be integrated into broader sustainability transformation strategies that combine technological investment with organisational readiness, governance structures, digital infrastructure, and sustainability-oriented strategic alignment. This interpretation is consistent with prior work showing that AI readiness, organisational flexibility, and sustainability-oriented management capabilities jointly shape long-term value creation in technology-intensive environments [37,96].

For managers, this implies that AI projects should be evaluated not only in terms of short-term efficiency gains, but also in relation to broader sustainability objectives such as resilience, resource coordination, circularity, and long-term adaptive capability. In practice, this requires integrating sustainability KPIs into AI implementation processes and promoting coordination between technical, operational, and sustainability-oriented decision structures.

From an implementation perspective, organisations should focus not only on deploying AI applications but also on redesigning operational processes capable of integrating AI-generated insights into routine decision-making. Investments in AI technologies without corresponding operational transformation are therefore unlikely to deliver sustained sustainability value. This interpretation reinforces the mechanism-based process model proposed in this review, according to which sustainable value emerges from the organisational embedding of AI-enabled mechanisms rather than from technological deployment alone.

For policymakers, the review highlights the importance of enabling conditions that support industrial AI adoption for sustainability purposes. Regulatory clarity, interoperability standards, digital infrastructure, and targeted incentives may help firms move beyond isolated efficiency projects towards broader sustainability-oriented AI applications. Such support becomes particularly relevant in contexts characterised by uneven digital maturity, high implementation costs, or fragmented supply-chain coordination. These implications are particularly relevant in the context of SDG 9, SDG 12, and SDG 13, where AI-enabled industrial transformation increasingly intersects with decarbonisation, responsible production, and climate action agendas.

Overall, the practical implication emerging from the review is that AI-enabled mechanisms contribute to sustainability value creation when managed as a socio-technical and organisational capability rather than as a purely technical solution.

5.5. Limitations

This review has several limitations that should be considered when interpreting its findings. First, the search strategy focused exclusively on peer-reviewed journal articles published between 2020 and 2025. Although this strengthened conceptual consistency and analytical rigour, it excluded conference proceedings and other early-stage publication formats where rapidly evolving AI research often appears first. Similar scoping choices are common in AI-sustainability reviews, but they may reduce sensitivity to emerging developments and experimental applications [93,97].

Second, the search strategy was deliberately oriented towards sustainability and industrial contexts. This may have reinforced the predominance of operational and environmental sustainability perspectives while comparatively underrepresenting social, governance, and ecosystem-level sustainability dimensions. Consequently, the final corpus provides stronger evidence regarding operational sustainability value creation than broader transformation-oriented sustainability dynamics.

Third, the computational screening process relied on prioritisation and term-matching procedures rather than full semantic interpretation. Although manual validation and inter-reviewer reliability checks mitigated this limitation, some relevant studies may still have been under-prioritised during the screening stages. Previous work on AI-related literature reviews similarly notes that scope limitations and keyword-based strategies may leave contextual dimensions insufficiently captured [93].

Finally, the proposed framework remains conceptual and interpretive rather than empirically validated. Although it synthesises the principal explanatory dimensions emerging from the literature, further empirical testing through case studies, longitudinal designs, surveys, and comparative industrial analyses is necessary to examine whether the proposed mechanisms and contingencies operate similarly across different organisational and institutional contexts.

5.6. Future Research Directions

The review suggests several promising directions for future research. First, future studies should move beyond application mapping and examine more explicitly how AI-enabled mechanisms are translated into broader forms of sustainability value across organisational and systemic levels. This requires longitudinal, multilevel, and comparative designs capable of examining when operational improvements remain local and when they evolve into resilience, circularity, or broader sustainability transformation processes. Recent work on industrial sustainability and AI similarly calls for stronger attention to governance, coordination, and transdisciplinary integration rather than purely technical optimisation [93,97].

Second, the field would benefit from more detailed theorisation and empirical testing of the organisational conditions enabling or constraining sustainability value creation. Future research should examine how data quality, digital maturity, interoperability, managerial support, and sustainability-oriented strategic alignment shape the effectiveness of AI-enabled prediction, optimisation, monitoring, and decision-support mechanisms across industrial contexts [24].

Third, future research should broaden the sustainability lens beyond operational efficiency and emissions reduction. Social sustainability, governance, workforce implications, accountability, resilience, and ecosystem-level transformation processes remain comparatively underdeveloped within the current literature. Integrating these dimensions would support a more comprehensive understanding of the sustainability implications of industrial AI adoption [83].

Fourth, future research should further examine the sustainability implications of AI itself. As industrial AI adoption expands, increasing attention must be devoted to

the environmental footprint of AI infrastructures, energy consumption associated with computational systems, governance implications, and potential rebound effects linked to digital optimisation processes. Integrating “AI for sustainability” with “sustainability of AI” perspectives would contribute to a more balanced and critically informed research agenda.

Finally, future empirical work should validate and refine the proposed framework across different industrial sectors and institutional contexts [22]. Case studies, survey-based research, mixed-method designs, and longitudinal analyses may help clarify how antecedent conditions, AI-enabled mechanisms, contingency factors, and sustainability outcomes interact over time and across organisational levels.

6. Conclusions

This systematic literature review examined how artificial intelligence has been conceptualised as a driver of sustainability value creation in industrial systems. Based on the analysis of 75 peer-reviewed studies published between 2020 and 2025, the review shows that the literature has expanded rapidly in recent years but remains predominantly centred on technical optimisation, operational efficiency, and process-level sustainability improvements [3,5,14]. While substantial evidence exists regarding where AI is applied and which sustainability outcomes are achieved, considerably less attention has been devoted to explaining how these outcomes emerge through organisational processes and under which conditions they can be sustained over time.

By synthesising the evidence across application domains, sustainability outcomes, AI-enabled mechanisms, antecedent organisational conditions, and contextual contingencies, this review moves beyond descriptive mapping towards a process-oriented explanation of AI-enabled sustainability value creation. The findings suggest that sustainability value should not be understood as a direct consequence of AI deployment. Rather, it emerges when AI-enabled mechanisms—including prediction, optimisation, monitoring, and decision support—become embedded into operational transformation processes supported by appropriate organisational capabilities and contextual conditions [8,10,11].

The principal theoretical contribution of this study is the development of a mechanism-based process model that integrates these relationships into a coherent explanatory framework. The proposed framework conceptualises AI-enabled sustainability value creation as a dynamic, organisationally embedded, and multilevel process linking organisational antecedents, AI-enabled mechanisms, operational transformation, sustainability outcomes, organisational learning, and contextual contingencies. In doing so, the study helps explain why similar AI technologies may produce different sustainability outcomes across industrial settings and contributes to the growing literature on AI-enabled industrial transformation by offering a more integrated understanding of sustainability value creation. This perspective addresses the conceptual fragmentation identified in previous reviews by providing a coherent explanation of how AI-enabled sustainability value is generated, organisationally embedded, and sustained across industrial systems [4,5,8].

From a practical perspective, the findings indicate that organisations should avoid viewing AI primarily as a technological solution for operational optimisation. Instead, successful AI-enabled sustainability strategies require organisational readiness, effective governance, operational redesign, and the integration of AI-generated insights into routine decision-making processes [6,8,10]. Organisations should therefore focus not only on deploying AI applications but also on redesigning operational processes capable of integrating AI-generated insights into routine decision-making. Sustainable value therefore depends not only on technological capability but also on the organisational capacity to transform AI-generated knowledge into continuous operational and strategic improvement.

Although this review followed a rigorous and transparent methodology, it remains subject to limitations inherent in systematic literature reviews, including the selected databases, publication period, language restrictions, and the rapidly evolving nature of the field. Future research should further investigate the dynamic relationships between AI-enabled mechanisms, organisational transformation, governance, resilience, and long-term sustainability performance through longitudinal, comparative, and multi-level empirical studies.

Overall, this study contributes to a more coherent understanding of AI-enabled sustainability value creation in industrial systems by demonstrating that sustainable value emerges through organisationally embedded transformation processes rather than through technological deployment alone. As industrial AI continues to evolve, developing a deeper understanding of these organisational mechanisms will be essential for advancing both theory and sustainability-oriented industrial practice.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18146948/s1>. File S1: Detailed search strategy and review protocol information. File S2: Screening and coding framework. File S3: Computational support scripts. File S4: Data extraction codebook. File S5: Final analytical corpus (n = 75). File S6: PRISMA 2020 checklist.

Author Contributions: Conceptualisation, D.M.; methodology, D.M. and P.S.; validation, D.M., P.S., F.M., B.D. and N.N.; formal analysis, D.M., P.S., F.M., B.D. and N.N.; investigation, D.M., P.S., F.M., B.D. and N.N.; data curation, D.M. and P.S.; visualisation, D.M. and P.S.; writing—original draft preparation, D.M. and P.S.; writing—review and editing, D.M., P.S., F.M., B.D. and N.N.; supervision, D.M.; project administration, D.M. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded by ISLA Santarém—Polytechnic University.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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