Article de Recherche
Research Article

Intelligent Circular Aviation: AI-Enabled Strategies for Sustainable Aircraft End-of-Life Management

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RÉSUMÉ

Cet article examine la contribution de l'intelligence artificielle (IA) à la gestion de la fin de vie (FV) des aéronefs, en s'articulant autour des stratégies de réduction, de réutilisation, de valorisation, de recyclage et de mise en décharge. Grâce à une revue systématique de la littérature couvrant la période 2015-2025 et à l'analyse de 76 articles sélectionnés, cette étude identifie comment les technologies numériques et intelligentes facilitent la prise de décision, la traçabilité et l'optimisation de la logistique inverse. Les résultats révèlent une prédominance des stratégies de réduction (28 %) et de recyclage (26 %), tandis que la réutilisation (21 %) et la valorisation (22 %) restent relativement peu explorées malgré leur potentiel plus élevé de préservation de la valeur. La présence marginale de la mise en décharge (3 %) confirme son exclusion progressive des modèles durables. Les résultats mettent en évidence un décalage partiel entre l'accent mis par la théorie et la logique spécifique de création de valeur du secteur aéronautique. L'article propose un cadre analytique intersectoriel intégrant des outils basés sur l'intelligence artificielle et une approche fondée sur le cycle de vie afin de renforcer la gestion durable de la fin de vie des aéronefs.

***Mots-clés** : Gestion de la fin de vie des aéronefs, intelligence artificielle, prise de décision, développement durable.*

ABSTRACT

This article examines the contribution of artificial intelligence (AI) to aircraft end-of-life (EOL) management, structured around the strategies of reduce, reuse, recover, recycle, and landfill. Through a systematic literature review covering 2015–2025 and analyzing 76 selected articles, this study identifies how digital and intelligent technologies support decision-making, traceability, and reverse logistics optimization. The results reveal a dominance of reduction (28%) and recycling (26%) strategies, while reuse (21%) and recovery (22%) remain comparatively underexplored despite their higher value-retention potential. The marginal presence of landfill (3%) confirms its progressive exclusion from sustainable models. The findings highlight a partial misalignment between

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theoretical emphasis and the specific value-creation logic of the aviation sector. The article proposes a cross-sectoral analytical framework integrating AI-enabled tools and lifecycle thinking to strengthen sustainable aircraft end-of-life management.

***Keywords**: Aircraft End-of-Life Management, Artificial Intelligence, Decision-Making, Sustainability.*

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INTRODUCTION

The aviation industry is entering an important phase of its sustainability transition, where the environmental footprint of aircraft can no longer be addressed solely through operational efficiency, alternative fuels, or propulsion technologies (Asmatulu et al., 2013; Khan et al., 2022). With thousands of commercial aircraft expected to reach retirement age over the coming decades, aircraft end-of-life (EOL) management is emerging as a strategic and unavoidable challenge (Keivanpour et al., 2013; Mofokeng et al., 2020). While significant efforts have been directed toward improving fuel efficiency, alternative propulsion systems, and operational optimization, aircraft end-of-life (EOL) management remains a relatively underexplored yet critical driver of sustainability (Khan et al., 2013). Aircraft dismantling, the reuse of serviceable components, material recovery, and recycling are complex processes involving multiple stakeholders, stringent safety requirements, and heterogeneous material flows, making EOL management a systemic challenge rather than a purely technical one (Arockiam et al., 2018).

Within the broader transition toward a circular economy, end-of-life strategies are no longer confined to waste treatment considerations but increasingly shape upstream decisions regarding product design, procurement, business models, and supply chain configuration (Al-Qazzaz et al., 2025). Evidence from multiple industrial sectors indicates that effective EOL performance is largely determined by prioritizing reduction and reuse strategies, supported by recovery and recycling pathways, while landfill disposal is increasingly excluded from sustainable system designs (EASA, 2023). However, translating these principles into operational practice in capital-intensive and safety-critical industries such as aviation requires advanced coordination, reliable information, and robust decision-making frameworks (Latrémouille-Viau, 2009).

Recent advances in digital technologies, artificial intelligence (AI), Industry 4.0, blockchain, and digital twin architectures offer unprecedented opportunities to address these challenges (Meske et al., 2022). Data-driven tools enable continuous lifecycle monitoring, predictive maintenance, component and material traceability, and the optimization of reverse logistics networks. (Bisswang et al., 2025; Hadjitchoneva, 2020). At the same time, multi-criteria decision-making methods, fuzzy logic, game-theoretic models, and life-cycle assessment approaches provide structured frameworks for evaluating end-of-life options under uncertainty, balancing environmental, economic, and operational objectives. Despite this growing body of research, literature remains fragmented. End-of-life strategies are often treated in isolation, digital technologies are discussed without explicit linkage to circular outcomes, and sector-specific insights are rarely synthesized into an integrated analytical framework applicable to aircraft end-of-life management (Maaß, 2020). This study addresses this gap by providing a structured cross-sectoral analysis of aircraft end-of-life management, explicitly grounded in the end-of-life framework reduce, reuse, recovery, recycle, landfill, and enriched by insights from digital transformation, circular business models, and decision-support systems (Yildizbasi et al., 2024).

This study investigates how digital and intelligent technologies, particularly artificial intelligence (AI), can support end-of-life (EOL) strategies and facilitate their implementation within the specific constraints of the aviation industry. It proposes an integrated EOL management framework illustrated through practical examples and analyzes its implications to identify methodological gaps and future research directions for more sustainable and optimized aviation practices. While previous reviews have addressed aircraft recycling, circular economy practices, digital transformation, and

AI applications separately, a review of the literature suggests that no previous study has systematically examined how AI-enabled technologies support the full spectrum of EOL strategies reduction, reuse, recovery, recycling, and landfill in the specific context of aircraft end-of-life management. This study fills this gap by developing an integrated analytical framework linking AI capabilities with EOL strategies.

I. CONTEXT OF AIRCRAFT END-OF- LIFE MANAGEMENT

End-of-life aircraft management has become a major strategic challenge for the aerospace industry, both economically and environmentally. The complexity of dismantling, recycling, and component recovery operations now requires innovative approaches to optimize processes, reduce costs, and minimize environmental impact (Khan et al., 2022). In this context, artificial intelligence (AI) is emerging as a promising technology capable of transforming how end-of-life aircraft are managed (Hadjitchoneva, 2020; Kılkış & Kılkış, 2017). Aircraft have a limited lifespan and consist of complex components and materials that may be difficult to recycle or reuse. End-of-life (EOL) management aims to reduce environmental impact, optimize resource recovery, and integrate sustainable practices into the aerospace industry (Agrawal & Singh, 2019; Khan et al., 2013).

Faced with climate pressure and resource scarcity, end-of-life management is becoming an essential lever for environmental and economic sustainability (Scheelhaase et al., 2022). It is crucial to integrate sustainability considerations from the outset of the business model design, rather than adding circular elements later. Design choices made during the manufacturing stage crucially determine whether products can be repaired, upgraded, and kept in service, thus influencing long-term end-of-life outcomes in a circular economy (Despeisse et al., 2022; Ipaki & Hosseini, 2025; Manea et al., 2024). This is why decisions made during the manufacturing phase play a decisive role in downstream environmental impacts, highlighting the importance of integrating sustainability assessment tools from the beginning of the product life cycle (Piron et al., 2025).

Digital technologies such as data analytics, IoT, and artificial intelligence are widely regarded by multiple stakeholders as key enablers of more sustainable and circular manufacturing systems. With the rise of emerging technologies, real-time monitoring and predictive analytics can improve the design and operational phases, thereby reinforcing a proactive approach to end-of-life management by maximizing product use before disposal (Kiran Sankar et al., 2024). Therefore, the adoption of smart technologies will enable a comprehensive overhaul of end-of-life product and equipment management systems, thereby accelerating the transition toward a more circular and sustainable economy. Effective end-of-life management of material-intensive products requires decision-support tools capable of managing uncertainty and conflicting sustainability criteria (Kiran Sankar et al., 2024; Zhuang et al., 2023). Similar to trends observed in many sectors such as space robotics, high-performance aerospace systems frequently prioritize operational adaptability and resilience over end-of-life planning, thus reinforcing the need to integrate lifecycle thinking into aircraft end-of-life management frameworks (Rahimi Nohooji & Voos, 2025). The challenges identified in the recycling of smart textiles are highly comparable to those observed in aircraft end-of-life management, where the integration of hybrid materials and embedded functionalities considerably complicates dismantling and material separation processes (Keivanpour, 2021; Tadesse et al., 2025). The difficulties encountered in sorting used batteries provide valuable information for aircraft end-of-life management, where component heterogeneity, integrated energy storage systems, and safety constraints also complicate dismantling and material separation processes (El Jalbout & Keivanpour, 2024; Kar & Chu, 2025). Insights from the design for disassembly and recycling of lithium-ion batteries are highly transferable to aircraft end-of-life management, where complex assemblies, safety constraints, and critical materials require early integration of end-of-life considerations (Espeute et al., 2024).

II. ARTIFICIAL INTELLIGENCE IN END-OF-LIFE MANAGEMENT

Recent work highlights the role of AI in the predictive analysis of component residual value, automation of maintenance diagnostics, and intelligent planning of end-of-life operations (Elahi et al., 2023). These advances offer significant opportunities to improve the efficiency of end-of-life management processes, while reducing the risk of human error and optimizing resource allocation (Eom et al., 2025; Paraschos et al., 2025). With the proliferation of data in the digital age, artificial intelligence (AI) plays an increasingly important role in reducing human intervention and extracting information effectively and efficiently (Duan et al., 2019). AI provides the information processing capabilities necessary for data integration and analysis, thus establishing a foundation for decision support, autonomous decision-making, and operational implementation (Amanollahnejad et al., 2026). End-of-life management is one of the many areas that have significantly evolved since the emergence of AI (Duan et al., 2019; Kurrahman, Tsai, Lim, et al., 2025).

Artificial intelligence and big data analytics significantly enhance decision-making processes in aircraft end-of-life management by enabling data-driven reverse logistics strategies aligned with the Triple Bottom Line framework. Through the systematic collection and analysis of dandailed data related to aircraft components and material compositions, AI-based systems support informed assessments of end-of-life disposition options (Agrawal & Singh, 2019). Predictive models further allow the evaluation of reuse and recycling potential by considering critical parameters such as component age, operational wear, and material characteristics. In addition, the automation of reverse logistics planning optimizes material and component flows by simultaneously reducing costs, minimizing processing time, and lowering environmental impacts (Ben-Assuli, 2021). This integration of AI-driven analytics strengthens sustainable disposition decisions and improves the overall efficiency, transparency, and resilience of aircraft end-of-life supply chains.

Artificial intelligence plays a central role in advancing circular end-of-life strategies by directly supporting reduction, reuse, and recovery objectives through enhanced resource optimization, asset performance, and lifecycle extension. By automating data analysis and enabling data-driven decision-making, AI significantly improves resource efficiency across complex industrial systems (Sjödin et al., 2023; Widjaja et al., 2025). The development of AI-enabled circular business models, particularly within digitally driven servitization frameworks, allows for prolonged product lifespans and intensified asset utilization. Through perceptive, predictive, and prescriptive capabilities, AI enhances condition monitoring, maintenance optimization, and performance management throughout the entire lifecycle of assets (Gabryelczyk et al., 2024). These capabilities strengthen decision-making processes by leveraging large-scale data analytics, thereby facilitating more effective circularity-oriented strategies and reinforcing sustainable end-of-life management pathways.

II.1 AI and sustainability

This review highlights how emerging digital technologies such as IoT, artificial intelligence, and blockchain support circular economy practices in transportation infrastructure by optimizing resource flows and reducing waste, an approach that resonates with the imperative to minimize environmental impacts in aircraft end-of-life systems (Yildizbasi et al., 2024).

(Shahzad et al., 2024) Highlight, based on empirical evidence, that artificial intelligence capabilities have a positive influence on the digital transformation of Chinese semiconductor companies, which in turn contributes to improving the performance of green supply chains (Shahzad et al., 2024). These results illustrate the structuring role of digital technologies in supporting sustainability goals, complementing strategies aimed at reducing environmental impacts and strengthening sustainable end-of-life management practices for products.

Leveraging big data combined with artificial intelligence fosters greater process integration within green supply chains, particularly by facilitating the coordination of reverse logistics flows related to the collection, sorting, and processing of end-of-life products (Benzidia et al., 2021). This increased integration acts as a key mediating mechanism in improving environmental performance, enabling better visibility of return flows, more efficient resource allocation, and optimized decisions regarding reuse, recycling, and recovery.

From an extended dynamic capabilities perspective, generative AI enhances green supply chain management by strengthening sensing, seizing, and reconfiguring capabilities, thereby supporting sustainability-oriented decision-making across complex supply networks (Kurrahman, Tsai, Lim, et al., 2025).

Firm-level empirical evidence indicates that intelligent manufacturing significantly reduces industrial pollution, highlighting the potential of AI-enabled production systems to support reduction-oriented sustainability objectives across the industrial lifecycle (Wang et al., 2025).

The proposed framework highlights digital technologies as key enablers of green manufacturing practices, suggesting that data-driven and intelligent systems can indirectly support sustainable end-of-life outcomes through enhanced lifecycle integration (Despeisse et al., 2022).

The transition toward circular systems increasingly depends on the integration of sustainability objectives into business models, governance mechanisms, and innovation strategies. Circular entrepreneurship, responsible production systems, and ecosystem-based approaches demonstrate that long-term environmental performance is enhanced when reduction, reuse, recovery, and recycling are considered simultaneously rather than as isolated initiatives (Henry et al., 2020; Dumitrica et al., 2023; Haseli et al., 2024).

II.2. AI and tools decision making

AI-powered digital twin technology can be used in real-time data analysis and predictive modeling to improve operational efficiency and inform maintenance and end-of-life decisions by integrating BIM with digital twin technologies in BIPV systems (Wang et al., 2024). This is directly applicable to aircraft end-of-life management. The integration of virtual sensors into digital twins enables the implementation of dynamic and data-driven life cycle analysis, paving the way for real-time environmental optimization of manufacturing processes and better anticipation of end-of-life impacts (Piron et al., 2025).

Hybrid decision-support methodologies, such as approaches integrating DEMATEL, ISM, and MICMAC, provide structured frameworks for prioritizing sustainability factors (Sumrit, 2025). They offer relevant support for guiding the deployment of digital and intelligent tools within end-of-life management systems, facilitating more coherent decision-making based on the interactions between key factors. Advanced embedded technologies and intelligent sorting systems developed for end-of-life battery management; highlight the potential of artificial intelligence-based classification and decision-support tools to improve the efficiency of aircraft dismantling and material recovery processes (Kar & Chu, 2025).

Analyzing social media data provides a data-driven approach to assessing the perceived effectiveness of product-service systems. Highlights barriers and facilitators to product access from the end-user perspective, dimensions often underrepresented in conventional end-of-life management assessments (Pourranjbar & Shokouhyar, 2023). Data-driven intelligent decision models enhance supplier selection robustness, indirectly strengthening end-of-life performance through upstream alignment and resilience integration (Gholami et al., 2025). Fuzzy logic-based multi-criteria decision models constitute robust tools for evaluating and prioritizing end-of-life options, particularly in contexts marked by uncertainty, imprecise data, and the subjectivity of stakeholder judgments (Pamucar et al., 2024). The study reports the design and in-orbit performance of a COTS-based intelligent camera system that autonomously identifies an uncooperative target and supports controlled rendezvous maneuvers, illustrating the role of vision-enabled autonomy in end-of-life service operations (Kimura et al., 2021). By promoting shared data spaces and interoperable platforms, Industry Commons provide foundational conditions for the deployment of AI-driven decision-support systems in complex end-of-life management environments (Magas & Kiritsis, 2022).

Digital technologies such as artificial intelligence, the Internet of Things, and data analytics act as key enablers of circular transition by improving traceability, decision-making, and coordination across product life cycles (Hassan et al., 2025). Digital innovations, including data platforms and AI-enabled coordination tools, play a critical role in enabling circular plastic value chains by improving traceability, stakeholder coordination, and data-driven end-of-life decision-making (Oyinlola et al., 2022). Digital transformation, supported by data analytics and artificial intelligence, enables firms to monitor lifecycle performance, anticipate end-of-life scenarios, and optimize circular value creation (Okorie et al., 2023). Digitalized procurement processes supported by data analytics and AI enable informed supplier selection and contract design, thereby strengthening end-of-life planning and reverse logistics integration (Bag et al., 2020).

Although artificial intelligence is not explicitly addressed, the complexity of material selection and circular design highlighted in this study of suggests strong potential for AI-driven decision-support systems in optimizing end-of-life material pathways (Omar et al., 2025a). Data-driven regional benchmarking of circular economy practices (Tsai et al., 2025) highlights the value of analytics-ready governance, thereby motivating the use of AI-enabled decision support to prioritize end-of-life interventions where gaps are most acute (Tsai et al., 2025). Smart PSS architectures provide a data-rich foundation for AI-enabled lifecycle monitoring and risk anticipation, supporting informed decision-making across use, maintenance, and end-of-life stages (Coba et al., 2024).

Supply chain readiness and maturity in smart technologies constitute prerequisite conditions for the effective deployment of AI-driven tools supporting end-of-life decision-making and reverse logistics coordination (Demir et al., 2023). Multi-sided digital platforms of (Franzò & Urbinati, 2023) provide a scalable foundation for AI-enabled coordination, matchmaking, and optimization of end-of-life resource loops across heterogeneous industrial actors. Collaborative circular ecosystems create favorable conditions for AI-enabled platforms that coordinate actors, optimize resource loops, and support end-of-life decision-making (Evertsen & Knotten, 2024). Emerging digital ecosystems provide new opportunities for intelligent end-of-life coordination beyond conventional manufacturing sectors. Data-rich environments, autonomous monitoring systems, and collaborative circular business models facilitate information sharing, operational visibility, and decision support across increasingly complex end-of-life networks (Kimura et al., 2021; Scipioni et al., 2023).

II.3. Aviation-Specific AI Applications

II.3.1 Digital Twin for aircraft retirement planning

Digital twins can provide a virtual representation of aircraft throughout their operational life, enabling the prediction of component degradation, maintenance history tracking, residual value estimation, and retirement scenario simulation (Wang et al., 2024, Piron et al., 2025). In aircraft EOL management, digital twins could support retirement planning by identifying optimal dismantling dates, estimating component recovery potential, and evaluating environmental impacts through dynamic lifecycle assessment (Okorie et al., 2023, Espeute et al., 2024).

II.3.2 AI-based residual value prediction for Used Serviceable Materials (USM)

Used Serviceable Material (USM) constitutes one of the most valuable outputs of aircraft end-of-life operations. AI-based predictive models could estimate the future market value of recovered components based on (Elahi et al., 2023) maintenance records, flight cycles, operational environments, repair history, and demand forecasting (Agrawal & Singh, 2019, Scheelhaase et al., 2022, Gholami et al., 2025). Typical examples include CFM56 engines, landing gear assemblies, auxiliary power units (APUs), and avionics systems.

II.3.3 Computer Vision for part identification and condition assessment

Computer vision systems could automatically identify aircraft components during dismantling operations (Kimura et al., 2021). Typical applications include automatic recognition of part and serial numbers, corrosion detection, crack identification, and classification of recoverable components. Vision-enabled systems could significantly reduce manual inspection time while improving traceability and reducing identification errors (Manea et al., 2024; Kar & Chu, 2025).

II.3.4 AI-assisted dismantling optimization

Aircraft dismantling involves thousands of heterogeneous components with different recovery values, safety constraints, and recycling pathways (Keivanpour, 2021). AI-based optimization algorithms could determine the most efficient dismantling sequence by simultaneously considering component value, accessibility, labor requirements, environmental impact, and certification constraints (Agrawal & Singh, 2019; Kar & Chu, 2025; Piron et al., 2025). For instance, an Airbus A320 has several thousand reusable components. AI can optimize dismantling sequences by prioritizing components according to their reuse, recovery, or recycling potential.

II.3.5 Predictive traceability and component history analysis

Aircraft component reuse depends on complete traceability and documented maintenance histories. AI-enabled traceability systems combining blockchain, digital records, and predictive analytics could continuously evaluate component health and certify reuse eligibility at retirement. For example: for a recovered hydraulic pump we have the maintenance history; flight cycles; ADs; repairs and operating environment. AI can automatically assess reuse eligibility, identify required repairs, and determine appropriate recycling pathways. The “table 1” below summarizes Aviation-Specific AI Applications and the expected benefits

Table 1: Mapping Artificial Intelligence Applications to Aircraft End-of-Life Objectives and Expected Benefits

AI Application	Aviation EOL Objective	Expected Benefits
Digital Twin	Retirement planning	Lifecycle optimization
Predictive Analytics	USM valuation	Higher value recovery
Computer Vision	Part identification	Faster inspection
Optimization Algorithms	Dismantling sequencing	Reduced costs
Blockchain + AI	Traceability	Regulatory compliance

III. METHODOLOGY

In this study, a methodology similar to that employed when studying RFID-enabled healthcare applications and issues was adopted (Wamba et al., 2013). The research timeframe covers the literature on end-of-life management published between January 2015 and December 2025.

III.1 Research design

This study adopts a systematic literature review (SLR) approach to identify, classify, and analyze the contribution of artificial intelligence to end-of-life management strategies and their potential applicability to aircraft end-of-life management.

III.2 Search strategy

The literature search was conducted between October 27 and October 31, 2025. All retrieved references and abstracts were imported into EndNote for screening and management, a reference management software package. Subsequently, these articles were screened based on their abstracts to identify those relevant to our research objective related to end-of-life management and to identify duplicate articles across the different platforms. This work was completed on November 17, 2025. Two duplicates were identified, and 43 articles were excluded based on the abstract analysis.

Then, from November 20, 2025, to December 15, 2025, the 145 articles were fully analyzed, including those not related to end-of-life management. This analysis showed that 69 articles were not aligned with the research objective, including 28 conference papers, 4 state-of-the-art reviews, and 37 articles with no explicit connection to end-of-life management. The results and discussion were developed and consolidated between the end of this phase and February 2, 2026. This “table 2” below, shows the Literature Search Strategy.

Table 2: Literature search strategy

Element	Description
Databases	ScienceDirect, Taylor & Francis, Wiley
Period	2015–2025
Language	English
Document type	Peer-reviewed journal articles
Search string	("artificial intelligence" OR "AI") AND ("end-of-life management")

III.3 Justification of database selection

The search was conducted using the following string: "artificial intelligence"] AND "end of life management". This 10-year period is considered representative of the implementation of end-of-life management in key sectors of Industry 4.0. Three databases were consulted, namely: Taylors and Francis (24), ScienceDirect (163) and Wiley (3). ScienceDirect, Taylor & Francis, and Wiley were selected because they collectively cover the major journals in sustainability, circular economy, manufacturing systems, supply chain management, and digital transformation.

III.4 Inclusion and Exclusion criteria

“Table 3” below summarizes the inclusion and exclusion criteria applied during the article selection process to ensure the relevance, quality, and consistency of the studies retained for the systematic literature review.

Table 3: Inclusion and Exclusion criteria

Inclusion Criteria	Exclusion Criteria
Published between 2015 and 2025	Published before 2015
Peer-reviewed journal article	Conference papers
Explicit link with AI	Editorials
Explicit link with EOL management	Books
Full text available	No EOL relevance
English language	Duplicate articles

III.5 Screening procedure

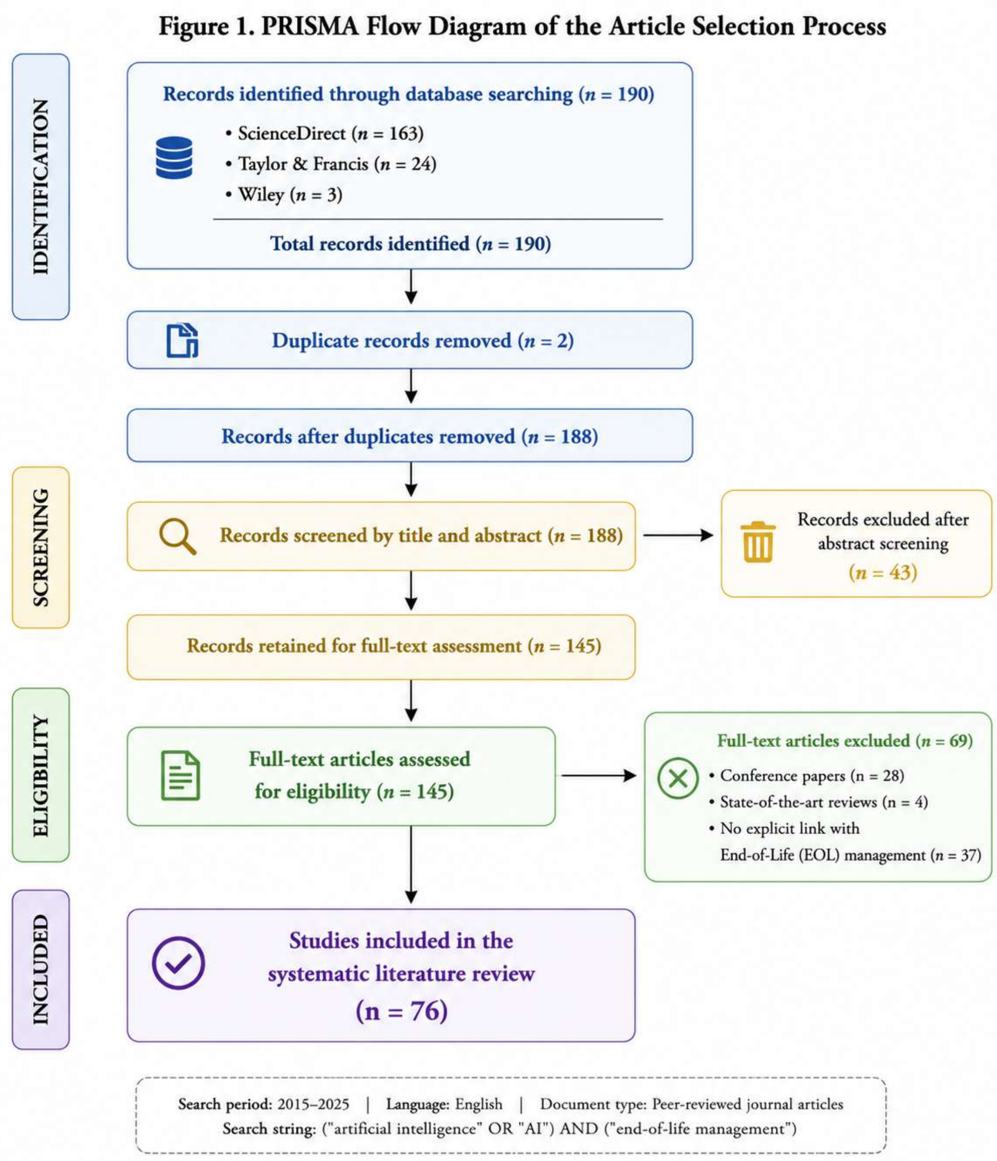
This "table 4" below, summarizes the different stages of the article selection process, from the initial identification of records to the final sample retained for analysis.

Table 4: Article selection process

Stage	Number
Records identified	190
Duplicates removed	2
Abstract screening exclusions	43
Full-text exclusions	69
Final sample	76

The article selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. "Fig. 1" summarizes the identification, screening, eligibility, and inclusion stages applied throughout the literature review process.

Figure 1: PRISMA Flow diagram



III.6 Quality assessment

A formal quality appraisal was conducted during the full-text screening stage. Each article was assessed according to four criteria: (1) relevance to the research objective, (2) methodological transparency, (3) explicit linkage to artificial intelligence or intelligent digital technologies, and (4) explicit connection with end-of-life management. Studies that did not sufficiently satisfy these criteria were excluded from the final sample. This quality assessment ensured the consistency, reliability, and relevance of the studies included in the review.

III.7 Article coding and classification process

Step 1 Full reading of each article

Step 2 Identification of dominant strategies

Step 3 Assignment to EOL categories

Many studies addressed multiple end-of-life (EOL) strategies simultaneously. During the coding process, articles were first mapped to all relevant EOL strategies identified in their content. However, for quantitative classification and statistical analysis, a dominant EOL strategy was assigned based on the primary focus and main contribution of each article. This approach avoided double counting while preserving the multidimensional nature of the reviewed studies. The percentages reported in the results section were calculated by dividing the number of articles assigned to each dominant EOL category by the total sample of 76 articles.

"Table 5" below presents the operational definitions of the End-of-Life (EOL) categories adopted in this study, adapted from circular economy and closed-loop management literature (Kara et al., 2022; Evertsen & Knotten, 2024).

Table 5: Operational definition of End-of-Life categories

Category	Definition
Reduce	Prevent waste generation
Reuse	Reuse without significant transformation
Recovery	Recover value, energy, or functionality
Recycle	Material transformation into secondary raw material
Landfill	Final disposal

Recovery includes both material recovery and value recovery pathways.

III.8 Sector classification

"Table 6" below, presents the sectoral distribution of the articles included in this review. The selected studies were classified according to their primary field of application in order to identify the industries where AI-enabled end-of-life management has received the greatest research attention. This classification provides a clearer understanding of the sectors driving current developments and highlights areas requiring further investigation.

Table 6: Sectoral distribution of the articles

Sector	Number of Articles
Aviation / Aerospace	10
Electronics & ICT	9
Batteries & Energy Storage	7
Construction & Built Environment	8
Manufacturing & Industrial Systems	25
Textile & Fashion	4

Waste Management & Recycling	13
Total	76

III.9 Identification of AI technologies

During the full-text analysis, the AI-enabled technologies reported in the selected studies were identified, extracted, and categorized according to their primary technological functions, as shown in "table 7".

Table 7: AI-enabled technologies

Raw Terms	Category
Predictive models	Predictive Analytics
Digital twins	Digital Twin
Intelligent cameras	Computer Vision
DEMATEL	Decision Support
Blockchain	AI Complementary Technologies

"Table 8" below presents the relationships identified between the main AI technologies and the different end-of-life strategies. The analysis highlights how specific technologies contribute to one or several EOL pathways, demonstrating the transversal role of AI in supporting circular and sustainable end-of-life management.

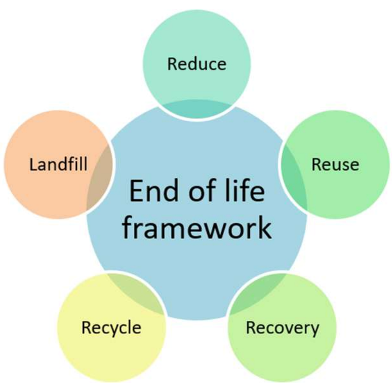
Table 8: Cross-Mapping Between AI Technologies and EOL Strategies

AI Technology	Reduce	Reuse	Recovery	Recycle	Landfill
Digital Twin	✓	✓			
Predictive Analytics	✓	✓	✓		
Computer Vision		✓	✓	✓	
Blockchain		✓	✓	✓	
Decision Support Systems	✓	✓	✓	✓	

IV. END-OF-LIFE FRAMEWORK

For this study, a classification framework was developed based on studies on end-of-life management in general, with a focus on artificial intelligence. According to several authors, end-of-life management is structured around five main independent components "Fig. 2", presented below:

Figure 2 : End of life Framework



IV.1 AI supporting Reduce strategies

The reviewed literature consistently identifies reduction as the dominant end-of-life strategy, reflecting a shift from waste treatment toward waste prevention. Across sectors, artificial intelligence contributes to reduction by improving resource efficiency, optimizing production systems, supporting predictive maintenance, and enabling data-driven decision-making (Henry et al., 2020; Legenvre et al., 2020). Studies on intelligent manufacturing, green supply chains, and digital transformation demonstrate that AI reduces material consumption, emissions, and operational inefficiencies through continuous monitoring and optimization (Despeisse & Acerbi, 2022; Shahzad et al., 2024; Wang et al., 2025).

A recurring finding is that the greatest sustainability gains are achieved during the design and planning phases. BIM-based decision-support systems, digital manufacturing frameworks, and Procurement 4.0 approaches integrate circularity criteria into upstream decisions, thereby reducing future waste generation and improving lifecycle performance (Bag et al., 2020; Al-Qazzaz et al., 2025). Similarly, circular business models and industrial ecosystems encourage organizations to minimize resource inputs while maximizing product utilization (Henry et al., 2020 ; Suppipat & Hu, 2022).

The literature further highlights the role of AI-enabled analytics in anticipating end-of-life challenges. Predictive models, intelligent planning systems, and digital twins improve forecasting accuracy and facilitate proactive interventions before products become waste (Kamble et al., 2021; Islam & Ali, 2025; Piron et al., 2025). Industry 4.0 technologies and smart manufacturing systems also reinforce reduction objectives by improving production efficiency and supporting environmentally responsible product evolution (Kusiak, 2022 ; Duan et al., 2024).

Beyond operational optimization, several studies emphasize that organizational maturity, digital readiness, and dynamic capabilities are critical conditions for achieving reduction objectives. Data-driven governance structures, smart supply chain capabilities, and continuous improvement mechanisms enable organizations to anticipate resource inefficiencies, reduce process waste, and support proactive sustainability-oriented decision-making throughout product lifecycles (Demir et al., 2023; Kurrahman, Tsai, Sethanan, et al., 2025; Sarfo et al., 2025).

The reduction perspective is also reinforced by broader sustainability frameworks that prioritize resource efficiency, low-carbon production, and waste prevention throughout the lifecycle. Studies examining manufacturing systems, product use phases, and net-zero production pathways indicate that environmental benefits are maximized when material consumption and waste generation are minimized before end-of-life options become necessary (Cossutta et al., 2022; Okorie et al., 2023; Pattanayak & Mavris, 2025).

Overall, reduction emerges as the foundational sustainability pathway because it directly addresses resource consumption and environmental impacts before products reach end-of-life. The predominance of reduction in the literature explains why it accounts for the largest share of the reviewed studies and serves as the entry point for most circular economy strategies.

Finally, end-of-life issues mainly through a reduce perspective, by emphasizing material efficiency, energy density improvement, and system lightweighting, while recycling and recovery are acknowledged as future challenges rather than fully developed strategies (Pattanayak & Mavris, 2025)

IV.2 AI supporting Reuse strategies

Reuse represents one of the highest value-retention strategies within circular economy systems because it preserves products and components in their original form. The literature shows that AI contributes to reuse primarily through predictive maintenance, condition monitoring, servitization, and lifecycle management systems. These technologies help organizations assess asset condition, identify reusable components, and extend operational lifetimes before replacement becomes necessary (Sjödin et al., 2023; Coba et al., 2024).

A major theme emerging from the reviewed studies is the transition from ownership-based models toward service-oriented business models. Servitization frameworks and smart product-service systems rely heavily on data analytics and AI-enabled monitoring to maximize asset utilization and prolong product life (Pourranjbar & Shokouhyar, 2023 ; Stabler et al., 2024). Through continuous performance tracking, organizations can implement maintenance interventions that prevent premature disposal and increase reuse opportunities (Orji et al., 2022; Tsai et al., 2025; Sumrit, 2025) .

Reuse opportunities are further strengthened by lifecycle intelligence technologies that improve visibility over asset condition, operational history, and remaining useful life. Digital lifecycle management approaches facilitate the identification of components suitable for extended use, refurbishment, or redeployment, thereby reducing premature replacement and supporting higher value-retention pathways (Coba et al., 2024; Wang et al., 2024).

Several studies also emphasize the role of design in enabling reuse. Sustainable product design, repair-oriented manufacturing, modular architectures, and design-for-disassembly approaches facilitate future reuse by improving accessibility, repairability, and adaptability (Li et al., 2021; Ipaki & Hosseini, 2025). Digital technologies further strengthen reuse by improving traceability and reducing information asymmetries across supply chains (Kiran Sankar et al., 2024 ; Hassan et al., 2025). By integrating end-of-life considerations into early design decisions (Al-Qazzaz et al., 2025), the BIM-based framework prioritizes reduction and reuse strategies, while recovery and recycling are evaluated as complementary pathways and landfill options are implicitly excluded.

These findings are particularly relevant to aviation. Aircraft components often retain substantial residual value after retirement, making reuse a strategically attractive option. Consequently, AI-enabled monitoring and lifecycle management technologies could play a critical role in identifying reusable parts, supporting certification processes, and maximizing value retention in aircraft end-of-life systems.

IV.3 AI supporting Recovery strategies

Recovery strategies focus on extracting residual value from products, materials, and components that cannot be directly reused. The reviewed literature highlights the growing importance of AI in supporting recovery operations through reverse logistics optimization, intelligent coordination, and resource valorization. Data-driven systems improve the identification, collection, and routing of end-of-life materials, thereby increasing recovery efficiency and reducing operational uncertainty (Agrawal & Singh, 2019 ; Benzidia et al., 2021).

Effective recovery systems depend not only on technological capabilities but also on the ability to coordinate complex resource flows across industrial ecosystems. Risk-aware circular supply chains, industrial symbiosis networks, and collaborative recovery infrastructures improve the capture of residual value while reducing uncertainty associated with end-of-life operations (Lahane & Kant, 2021a; Suppipat & Hu, 2022; Evertsen & Knotten, 2024).

Several studies demonstrate that AI-enabled supply chains and digital platforms improve collaboration among stakeholders involved in circular resource loops. Smart green supply chain management, collaborative ecosystems, and multi-sided digital platforms facilitate the coordination required to recover valuable materials and components across complex industrial systems (Franzò & Urbinati, 2023; Kim et al., 2025).

Recovery is also increasingly associated with advanced valorization pathways (Kara et al., 2022). Waste-to-hydrogen technologies, material recovery systems, and upcycling approaches transform end-of-life materials into valuable secondary resources, reducing dependence on virgin raw materials (Suppipat & Hu, 2022; Le et al., 2025 ; L. Zhang et al., 2025) . Similarly, studies on batteries, plastics, and industrial ecosystems highlight the economic and environmental benefits of recovering valuable resources before disposal becomes necessary (Oyinlola et al., 2022 ; Kar & Chu, 2025).

Advanced recovery pathways increasingly focus on preserving economic value through refurbishment, remanufacturing, upcycling, and secondary resource generation. These approaches demonstrate that end-of-life materials can become strategic inputs for new production systems, reducing dependence on virgin resources while improving circularity performance (Ciacci et al., 2020; Le et al., 2025; Y. Zhang et al., 2025).

Although recovery receives less attention than reduction, the literature increasingly recognizes it as a strategic pillar of circular economy systems. In aviation, where engines, avionics, alloys, and composite materials often retain significant residual value, recovery strategies supported by AI could substantially improve both economic performance and environmental sustainability.

IV.4 AI supporting Recycling strategies

Recycling remains one of the most mature and operationalized end-of-life strategies across industrial sectors (Magas & Kiritsis, 2022). The literature demonstrates that AI technologies significantly improve recycling performance through intelligent sorting, computer vision, automated classification, blockchain-enabled traceability, and advanced analytics (Jiang, Zhang, You, Van Fan, et al., 2023; Kar & Chu, 2025). These technologies increase material recovery rates while reducing contamination and operational costs (Zhang et al., 2019).

The effectiveness of recycling systems is increasingly associated with the integration of advanced assessment and optimization tools capable of evaluating environmental trade-offs, material quality, and recovery performance. Decision-support approaches facilitate the selection of the most sustainable recycling pathways while improving operational efficiency and resource valorization outcomes (Anshassi & Townsend, 2024; Pamucar et al., 2024).

A central theme emerging from the literature is the importance of intelligent sorting and material identification. Automated systems equipped with AI capabilities can rapidly classify materials and direct them toward appropriate recycling pathways, thereby improving efficiency and scalability (Manea et al., 2024; Tadesse et al., 2025). Similar benefits are observed in battery recycling, waste management, electronics, and photovoltaic modules, where technological complexity requires sophisticated decision-support tools (Aşkın et al., 2023; Xu et al., 2024). Effective end-of-life management in the fashion sector requires a hierarchical combination of waste reduction, reuse, and recycling strategies, while landfill disposal remains a critical issue to be minimized (Rehman et al., 2024).

The effectiveness of recycling is also strongly influenced by upstream design choices. Design-for-disassembly, modular product architectures, and sustainable material selection facilitate material separation and improve recycling outcomes (El Jalbout & Keivanpour, 2024; Omar et al., 2025a). Blockchain technologies further enhance recycling systems by improving transparency, traceability, and stakeholder coordination throughout end-of-life processes (Zhang et al., 2019; Jiang, Zhang, You, Fan, et al., 2023; Rehman et al., 2024).

Sector-specific studies further demonstrate that recycling remains a critical pathway for managing technologically complex products such as photovoltaic modules, batteries, smart textiles, and electronic equipment. In these contexts, technological innovation and policy support play a decisive role in improving recycling performance and reducing residual waste generation (Aşkın et al., 2023; Xu et al., 2024; Kumar & Shukla, 2025).

Despite its widespread adoption, recycling is increasingly viewed as a secondary strategy within the circular economy hierarchy. While it remains essential for recovering material value, recycling generally preserves less value than reuse or recovery. Consequently, the literature suggests that recycling should be integrated into broader circular systems rather than considered the ultimate sustainability objective.

IV.5 Why Landfill remains marginal

The Industry Commons perspective implicitly supports reduction, reuse, recovery, and recycling pathways by enabling cross-domain coordination and resource sharing at the ecosystem level (Magas & Kiritsis, 2022).

Emerging evidence also highlights that landfill remains primarily a residual outcome when technological, economic, or organizational barriers prevent higher-value circular pathways from being implemented. Even in sectors facing significant recycling challenges, stakeholders increasingly seek to minimize landfill dependence through improved recovery systems, policy interventions, and circular design practices (Anshassi & Townsend, 2024; Manikandan et al., 2024). Landfill is consistently portrayed as the least desirable end-of-life option and appears only marginally throughout the reviewed literature. Most studies explicitly or implicitly exclude landfill from sustainable circular economy frameworks because it destroys material value, generates environmental impacts, and conflicts with resource-efficiency objectives (Kara et al., 2022; Rehman et al., 2024).

The limited presence of landfill reflects the growing dominance of circular economy principles. Advances in AI, digital traceability, intelligent sorting, recovery technologies, and circular business models have created viable alternatives that prioritize reuse, recovery, and recycling over disposal (Dumitrica et al., 2023; Franzò & Urbinati, 2023). Regulatory interventions also contribute to landfill avoidance by encouraging material valorization and restricting environmentally harmful disposal practices (Xu et al., 2024).

Several studies identify landfill primarily as a residual outcome when higher-value circular pathways are unavailable. Even in sectors facing significant technical challenges, such as plastics, batteries, and smart textiles, researchers emphasize the need to minimize landfill through improved recovery and recycling systems (Van Fan et al., 2022; Kar & Chu, 2025; Tadesse et al., 2025).

For aviation, landfill is particularly incompatible with sustainability objectives because aircraft contain high-value metals, certified components, and advanced materials with significant reuse, recovery, or recycling potential. The marginal role of landfill therefore reflects a broader transition toward value-retention strategies and supports the conclusion that future aircraft end-of-life systems should prioritize intelligent circular pathways rather than final disposal.

V. RESULTS

V.1 AI Technologies and End-of-Life Strategies

The following "Table 9" illustrates how the main AI-enabled technologies contribute to the implementation of reduce, reuse, recovery, and recycling strategies.

Table 9: AI and EOL

AI Tool	Reduce	Reuse	Recover	Recycle
Digital Twin	✓	✓		

Predictive Analytics	✓	✓	✓	
Computer Vision		✓	✓	✓
Blockchain		✓	✓	✓
Decision Support Systems (DEMATEL, Fuzzy Logic, MICMAC)	✓	✓	✓	✓
Big Data Analytics	✓		✓	✓
Intelligent Optimization Algorithms	✓		✓	✓
Intelligent Sorting Systems			✓	✓
Smart Product-Service Systems (Smart PSS)	✓	✓		
AI-enabled Supply Chains	✓	✓	✓	

This table shows that Decision Support Systems represent the most versatile AI category, supporting all four circular strategies. Digital Twins and Smart Product-Service Systems are primarily associated with reduction and reuse by extending product lifetimes and improving lifecycle visibility. Computer Vision, Blockchain, and Intelligent Sorting Systems mainly contribute to recovery and recycling through traceability, automated identification, and material classification. Predictive Analytics emerges as a transversal technology supporting reduction, reuse, and recovery through condition monitoring and value prediction.

V.2 Sectoral Distribution of End-of-Life Strategies

The following "table 10" highlights the predominant end-of-life strategies addressed within each industrial sector included in the review.

Table 10: Sector and EOL

Sector	Reduce	Reuse	Recover	Recycle
Aviation / Aerospace	✓	✓✓	✓✓	✓
Electronics & ICT	✓	✓	✓	✓✓
Batteries & Energy Storage	✓		✓✓	✓✓
Construction & Built Environment	✓✓	✓✓	✓	✓
Manufacturing & Industrial Systems	✓✓	✓	✓	✓
Textile & Fashion	✓	✓		✓✓
Waste Management & Recycling			✓✓	✓✓

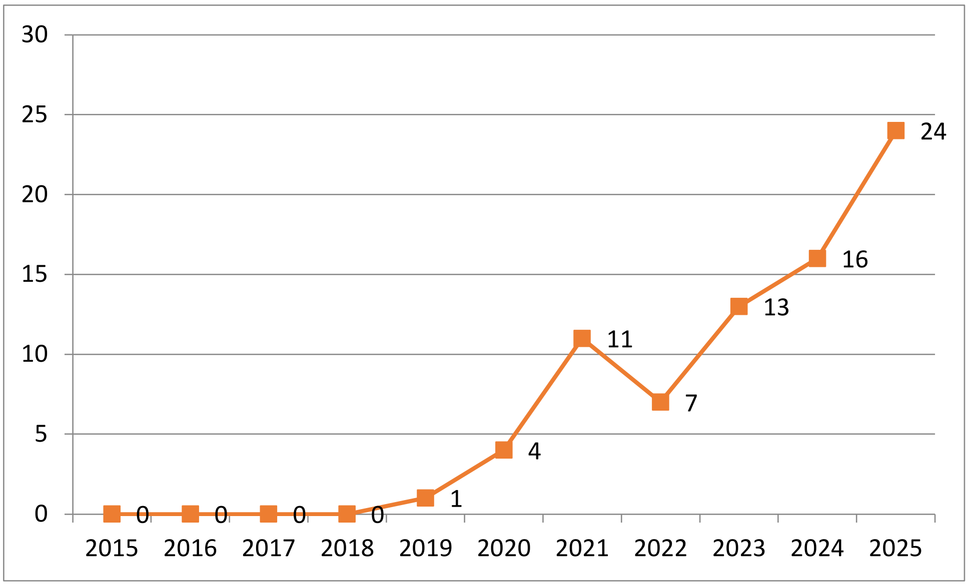
✓ = frequently addressed
✓✓ = dominant strategy in the sector

Sectoral analysis reveals important differences in the prioritization of end-of-life strategies. Aviation and construction sectors place stronger emphasis on reuse and recovery due to the high residual value of assets and components. Electronics, batteries, and waste management sectors focus predominantly on recycling and material recovery because of material complexity and regulatory requirements. Manufacturing studies are largely reduction-oriented, emphasizing resource efficiency and waste prevention. Textile studies mainly address recycling, while reuse is increasingly promoted through circular business models and digital traceability systems.

V.3 Temporal evolution of publications

This figure "Fig. 3" shows the distribution of articles according to their year of publication.

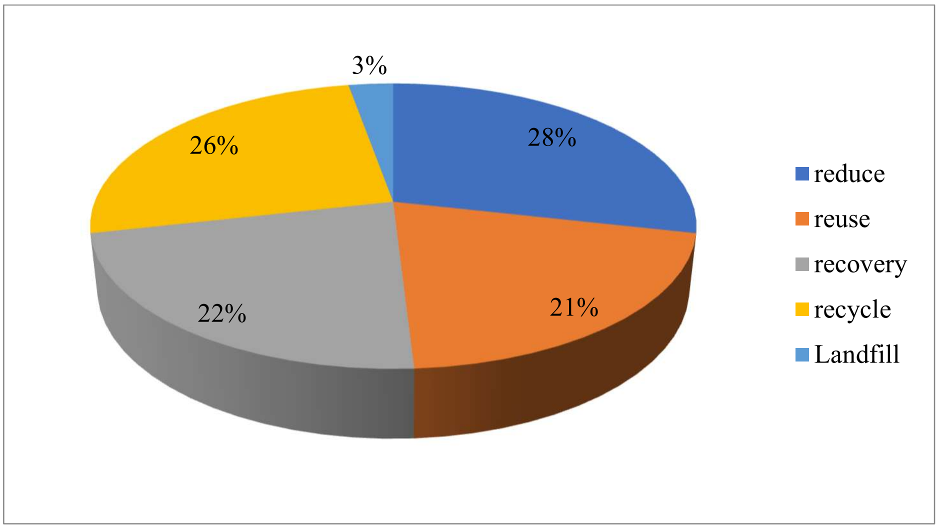
Figure 3 : Distribution of articles per year



V.4 Distribution of articles across End-of-life strategies

This figure "Fig. 4" shows the distribution of articles according to the end-of-life strategies used.

Figure 4 : Distribution of articles by end of life framework



V.5 Methodological approaches

This "table 11" shows the summary of articles by most methodological approach used.

Table 11: Distribution by most used approach

Most used approach	Reference	N°	%
Analytical approach	(Zhuang et al., 2023) , (Kamble et al., 2021) , (Lahane & Kant, 2021b), (Islam & Ali, 2025), (Pattanayak & Mavris, 2025); (Piron et al., 2025); (Pourranjbar & Shokouhyar, 2023); (Sumrit, 2025); (Van Fan et al., 2022); (Zhang et al., 2019), (Kurrahman, Tsai, Sethanan, et al., 2025),(Benzidia et al., 2021); (Cossutta et al., 2022); (Kiran Sankar et al., 2024); (Kumar & Shukla, 2025), (Demir et al., 2023); (Despeisse & Acerbi, 2022); (Hassan et al., 2025); (Kimura et al., 2021); (Kurrahman, Tsai, Lim, et al., 2025); (Oyinlola et al., 2022); (Wang et al., 2025) ; (Al-Qazzaz et al., 2025); (Ciacci et al., 2020); (Coba et al., 2024); (Dumitrica et al., 2023); (Franzò & Urbinati, 2023); (Kusiak, 2022); (Lahane & Kant, 2021a); (Legenvre et al., 2020); (Okorie et al., 2023); (Orji et al., 2022); (Sarfo et al., 2025); (Tsai et al., 2025); (Y. Zhang et al., 2025) , (Ahmed et al., 2023); (Bag et al., 2020); (Duan et al., 2024); (Evertsen & Knotten, 2024); (Haseli et al., 2024); (Henry et al., 2020); (Jiang, Zhang, You, Van Fan, et al., 2023); (Li et al., 2021); (Oluleye et al., 2023); (Xu et al., 2024), (Lin et al., 2020), (Saghafinia et al., 2024), (Gholami et al., 2025) ; (Keivanpour, 2021) ; (Paraschos et al., 2025) ; (Scheelhaase et al., 2022)	52	68.42
Reviews	(Aşkın et al., 2023); (Firoozi et al., 2025); (Le et al., 2025);(Mejía-Moncayo et al., 2025); (Omar et al., 2025b); (Pamucar et al., 2024); (Rehman et al., 2024); (Scipioni et al., 2023); (Sivasubramanian et al., 2024); (Wang et al., 2024); (Yildizbasi et al., 2024) ; (Kara et al., 2022) , (L. Zhang et al., 2025) ; (Elahi et al., 2023)	14	18,42
Case studies	(Anshassi & Townsend, 2024); (El Jalbout & Keivanpour, 2024); (van Eechoud & Ganzaroli, 2023), (Manea et al., 2024), (Suppipat & Hu, 2022)	5	6,58
Conceptual approach	(Stabler et al., 2024), (Sjödin et al., 2023), (Ipaki & Hosseini, 2025); (Magas & Kiritsis, 2022)	4	5,26
Survey study	(Shahzad et al., 2024)	1	1,32

V.6 Journal distribution

Forty-four journals were identified in this study as follows here in "table 12".

Table 12 : Distribution of articles per journal

Journals	N°	%
Journal of Cleaner Production	15	34,09
Sustainable Production and Consumption	5	11,36
Technological Forecasting & Social Change	5	11,36
Resources, Conservation & Recycling	4	9,09
International Journal of Production Research	3	6,82
Waste Management	2	4,55
Production & Manufacturing Research	2	4,55
Journal of Industrial and Production Engineering	2	4,55
Journal of Industrial and Production Engineering	2	4,55
Journal of Environmental Management	2	4,55

Advanced Sustainable System	2	4,55
The Journal of The Textile Institute	1	2,27
Technology Analysis & Strategic Management	1	2,27
Sustainable Energy Technologies and Assessments	1	2,27
Results in Engineering	1	2,27
Research-Technology Management	1	2,27
Renewable Energy	1	2,27
Next Sustainability	1	2,27
Materials Today Sustainability	1	2,27
Manufacturing Technology	1	2,27
Journal of Small Business Management	1	2,27
Journal of Manufacturing Science and Technology	1	2,27
Journal of Hazardous Materials	1	2,27
Journal of Control and Decision	1	2,27
International Journal of Production Economics	1	2,27
International Journal of Logistics Research and Applications	1	2,27
Industrial Management	1	2,27
Global Environmental Change	1	2,27
Engineering Management Journal	1	2,27
Engineering Applications of Artificial Intelligence	1	2,27
Energy Strategy Reviews	1	2,27
Energy Conversion and Management	1	2,27
Cybernetics and Systems	1	2,27
Cleaner Logistics and Supply Chain	1	2,27
Cleaner Engineering and Technology	1	2,27
Architectural Engineering and Design Management	1	2,27
Applied Mathematical Modelling	1	2,27
Applied Economics	1	2,27
Africa Journal of Management	1	2,27
Advanced Robotics	1	2,27
Advanced Materials Technologies	1	2,27
International Journal of Hydrogen Energy	1	2,27
Applied Energy	1	2,27
Advances in Electrical Engineering, Electronics and Energy	1	2,27

V.7 Artificial Intelligence technologies identified in the Literature

Seventeen artificial intelligence technologies were listed in this study as follows in “table 13”:

Table 13 : Distribution by different Artificial Intelligent technologies used

Category	AI / Intelligent Digital Technologies Mentioned	Role in End-of-Life Management
Artificial Intelligence (generic)	Artificial Intelligence (AI), AI-based systems, AI-enabled systems, AI-driven analytics, AI-driven decision-support systems	Decision support, analytical automation, optimization of end-of-life disposition choices
Big Data & Advanced Analytics	Big Data Analytics, data-driven analytics, large-scale data analytics, data-driven decision-making	Analysis of return flows, end-of-life visibility, optimized resource allocation
Predictive Modeling	Predictive models, predictive modeling, predictive maintenance	Assessment of reuse and recycling potential, anticipation of end-of-life scenarios

Advanced Analytical Capabilities	Perceptive, predictive, and prescriptive capabilities	Condition monitoring, maintenance optimization, prescriptive end-of-life decisions
Intelligent Optimization	Automated reverse logistics planning, resource optimization algorithms, intelligent flow optimization	Cost reduction, lead-time minimization, environmental impact reduction
Digital Twin	Digital twin technology, AI-powered digital twins	End-of-life simulation, impact anticipation, lifecycle optimization
BIM & Digital Integration	BIM integrated with digital twin	Support for maintenance and end-of-life decision-making
Intelligent Sensors	Virtual sensors, soft sensors, embedded data detection systems	Real-time data acquisition, dynamic LCA, anticipation of end-of-life impacts
Intelligent & Circular Supply Chains	AI-enabled green supply chain management, intelligent reverse logistics coordination	Coordination of end-of-life flows, improved environmental performance
Digital Platforms	AI-enabled coordination platforms, multi-sided digital platforms, data platforms	Multi-actor coordination, management of circular resource loops
Computer Vision & Autonomous Systems	Intelligent camera systems, vision-enabled autonomy, autonomous visual identification systems	Identification, sorting, and autonomous operations in end-of-life contexts
Fuzzy Logic Decision Models	Fuzzy logic-based decision models, fuzzy Frank weighted assessment model, Fuzzy-WINGS	Prioritization of end-of-life options under uncertainty
Hybrid Decision-Support Methods	DEMATEL, ISM, MICMAC	Structuring and ranking interdependent end-of-life factors
Generative Artificial Intelligence	Generative AI capabilities	Enhancement of dynamic capabilities and sustainability-oriented decision-making
Intelligent Sorting & Classification Systems	AI-based classification tools, intelligent sorting systems, advanced embedded technologies	Improved dismantling efficiency and material recovery
Smart Products & Product-Service Systems	Smart products, Smart Product-Service Systems (Smart PSS)	Product lifetime extension, failure prevention, indirect end-of-life benefits
AI-Complementary Technologies	Internet of Things (IoT), blockchain (as a data backbone for AI)	Traceability, data reliability, and trusted end-of-life decision support

VI. DISCUSSION

VI.1. Interpretation of End-of-Life Strategies distribution

The analysis reveals a differentiated but relatively balanced distribution of end-of-life strategies across the reviewed literature. End-of-life management has become an increasingly important research topic; since 2022, researchers and professionals have shown a growing interest in these questions surrounding end-of-life management. Reduction-oriented strategies represent the largest share (28%), confirming their central role in sustainability-oriented systems. Recycling follows closely (26%), highlighting the continued dominance of material recovery approaches in operational practice. Recovery (22%) and reuse (21%) receive comparable levels of attention in the literature, indicating growing but still secondary attention to value-retention strategies. In contrast, landfill accounts for only 3%, confirming its marginalization within contemporary circular economy research.

This distribution suggests that, while the literature increasingly embraces circular principles, a tension persists between preventive strategies (reduce, reuse) and downstream corrective approaches (recovery, recycle). The relatively strong presence of recycling reflects its technological maturity and regulatory acceptance, whereas reuse and recovery despite their higher value-retention potential, remain constrained by organizational complexity, information asymmetries, and coordination challenges.

From an aviation perspective, these results are particularly revealing. Aircraft end-of-life management is structurally aligned with reuse and recovery, given the high residual value of components and the stringent certification environment. However, the literature still places comparable or even greater emphasis on recycling, suggesting a misalignment between theoretical treatment and sector-specific value creation mechanisms. The marginal role of landfill is consistent with both regulatory pressures and the technical infeasibility of disposal for high-value aerospace materials.

VI.2. Implications for Aircraft End-of-Life Management

Although the reviewed studies originate from diverse industrial sectors, their findings provide valuable insights for aircraft end-of-life management. The results indicate that artificial intelligence can support several critical activities associated with aircraft retirement, including component traceability, residual value assessment, dismantling optimization, reverse logistics coordination, and decision-making under uncertainty.

The predominance of reduction-oriented strategies in the literature suggests that aircraft end-of-life performance should be considered from the earliest stages of aircraft design. Design-for-disassembly principles, digital product records, and lifecycle data continuity can significantly improve future recovery and reuse opportunities.

The prominence of reuse and recovery strategies in aviation-related studies reflects the substantial residual value retained by aircraft components. Engines, landing gear systems, avionics, and other certified parts often retain considerable economic value after aircraft retirement. AI-enabled predictive analytics and digital twin technologies could facilitate the identification of reusable components, estimate remaining useful life, and support certification processes for Used Serviceable Materials (USM).

The results also highlight the importance of traceability and information management. Aircraft end-of-life operations involve multiple stakeholders, including airlines, lessors, maintenance organizations, dismantling facilities, and recyclers. AI-supported platforms combined with blockchain and digital records could improve information sharing, enhance regulatory compliance, and reduce uncertainty during dismantling and material recovery operations.

Finally, the limited role of landfill in the reviewed literature confirms that future aircraft end-of-life systems should prioritize value-retention strategies. However, significant challenges remain for composite materials and complex assemblies, where economically viable reuse, recovery, or recycling pathways are still under development. Future research should therefore focus on sector-specific validation of AI-enabled solutions within real aircraft retirement projects.

VI.3 Implications for Practice

Beyond the cross-sectoral evidence identified in the literature, several AI-enabled applications appear particularly promising for aircraft end-of-life management. Digital twins may support retirement planning and lifecycle simulations, predictive analytics can improve the valuation of used serviceable materials (USM), computer vision may automate component identification and condition assessment, while AI-driven optimization can enhance dismantling operations and reverse logistics. These applications illustrate how the aviation sector can benefit from the broader digital transformation observed across other industries.

These findings carry several implications for industrial practice, particularly in aviation and other capital-intensive sectors. First, the dominance of reduction (28%) underscores the importance of upstream decision-making, including sustainable product design, procurement strategies, and lifecycle planning. For aviation stakeholders, this implies that end-of-life performance is largely determined well before aircraft retirement, reinforcing the need for design for disassembly, modular architectures, and data continuity throughout the aircraft lifecycle.

Second, the strong representation of recycling (26%) reflects its role as the most operationalized end-of-life strategy. While recycling remains essential, especially for metals and critical materials, it should not be treated as the primary circular solution in isolation. In aviation, overreliance on recycling risks undervaluing reuse and recovery pathways that preserve significantly higher economic and environmental value.

Third, the comparable shares of recovery (22%) and reuse (21%) point to an emerging but underexploited potential. Practitioners face practical barriers related to certification, traceability, and coordination across multiple actors. Here, digital technologies and AI-enabled decision-support systems emerge as critical enablers for identifying reusable components, optimizing reverse logistics, and reducing uncertainty in end-of-life decision-making.

Finally, the marginal role of landfill (3%) confirms its incompatibility with circular objectives. For aviation, this reinforces the need to further develop viable alternatives for composite materials and complex assemblies, where landfill remains a residual risk rather than a strategic option. These were drawn from forty-four journals and Seventeen artificial intelligence technologies were listed in this study.

VI.4 Implications for Future Research

The observed distribution of end-of-life strategies also highlights several avenues for future research. First, while reduction dominates the literature, empirical validation of its long-term impact on end-of-life outcomes remains limited, particularly in safety-critical sectors. Future studies should investigate how upstream design and procurement decisions quantitatively influence reuse, recovery, and recycling performance at aircraft retirement.

Second, the near parity between recycling, recovery, and reuse suggests a need to re-balance research efforts toward higher-value retention strategies. More empirical case studies, longitudinal analyses, and data-driven assessments are needed to understand the real-world feasibility of reuse and recovery in complex industrial systems.

Third, the relatively low integration of landfill in current research may obscure residual risks. Future research should explicitly address failure modes of circular systems, including scenarios where reuse, recovery, or recycling are not feasible, in order to design more resilient end-of-life strategies.

Finally, there is a strong need for integrated methodological frameworks combining life cycle assessment, artificial intelligence, multi-criteria decision-making, and policy analysis. Such approaches would allow researchers to move beyond static evaluations and toward dynamic, scenario-based modeling of end-of-life systems.

VI.5 Limitations of the Study

This study is subject to several limitations. First, the classification of articles according to dominant end-of-life strategies involves a degree of interpretative judgment, particularly when strategies are treated implicitly rather than explicitly. Second, although the review adopts a cross-sectoral perspective, sector-specific nuance, particularly those unique to aviation, may not be fully captured by the broader literature analyzed. Finally, the rapidly evolving nature of digital technologies and regulatory frameworks means that some findings may become outdated as new solutions and policies emerge.

CONCLUSION

Aircraft end-of-life management should no longer be regarded as a peripheral environmental issue but rather as a strategic pillar of aviation sustainability. This study demonstrates that artificial intelligence and digital technologies provide powerful enablers to operationalize circular end-of-life strategies, particularly through predictive modeling, digital twins, intelligent sorting systems, and data-driven decision-support tools. While reduction and recycling dominate current research, the aviation sector presents a structural opportunity to prioritize higher-value pathways such as reuse and recovery, given the significant residual value of aircraft components.

Bridging the gap between theoretical circular principles and sector-specific operational constraints requires integrated lifecycle thinking and early-stage design integration. Furthermore, enhanced traceability, interoperable data platforms, and AI-driven reverse logistics coordination are essential to overcome uncertainty and certification challenges. Future research should focus on empirical validation within aerospace contexts and the development of dynamic, scenario-based evaluation models. Ultimately, embedding AI within a hierarchical end-of-life framework offers a pathway toward more resilient, economically viable, and environmentally sustainable aircraft retirement systems.

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