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AI-SUPPORTED DECISION-MAKING FRAMEWORK FOR SUSTAINABLE CONSTRUCTION WASTE MANAGEMENT

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Abstract

Construction and demolition activities produce a large and growing share of global solid waste, creating environmental, economic, and regulatory challenges for the built environment. Traditional waste-management practices in construction are often reactive, fragmented, and decision-making is constrained by manual processes and limited data, which leads to inefficient material reuse and higher carbon footprints. This paper proposes an AI-supported Decision-Making Framework (AI-SDMF) designed to enable proactive, data-driven, and sustainable construction waste management. The framework combines a data-collection layer (site sensors, BIM and project lifecycle data, and waste manifests) with an AI analytical engine for classification, waste-quantity forecasting, and diversion-path prediction. Outputs feed a Decision Support System (DSS) that evaluates trade-offs across cost, embodied CO_2, and circularity metrics, while a feedback and optimization module (reinforcement/adaptive learning) continuously improve recommendations. A conceptual case scenario demonstrates how AI-SDMF can reduce waste generation, increase reuse and recycling rates, and lower environmental impacts compared with conventional approaches. The framework aims to aid contractors, waste managers, and policymakers in making transparent, timely, and sustainable decisions in construction waste management.

1. INTRODUCTION

Construction waste (CW) has emerged as one of the most critical environmental challenges confronting the global construction industry. The sector is responsible for nearly one-third of the world's total solid waste generation, with vast quantities of concrete, metals, timber, plastics, and other materials discarded during building, renovation, and demolition phases [1]. These waste streams not only deplete natural resources but also contribute significantly to land degradation, greenhouse gas emissions, and ecological imbalance. As governments worldwide intensify their sustainability commitments, efficient construction waste management (CWM) has become a central priority in advancing circular-economy goals and reducing the environmental footprint of the built environment. Despite increased awareness, most CWM practices remain highly fragmented and reactive [2]. Traditional approaches rely on manual data recording, limited material tracking, and human judgment to plan, sort, and dispose of waste. Such processes are time-consuming, prone to errors, and incapable of handling the large, complex datasets that modern construction projects produce. Moreover, decision-making in CWM is often based on cost minimization rather than holistic sustainability indicators such as embodied energy, recyclability, and life-cycle carbon impact [3]. As a result, opportunities for material reuse and waste minimization are frequently overlooked, undermining progress toward sustainable development objectives. The construction industry is currently undergoing rapid digital transformation through technologies such as Building Information Modeling (BIM), Internet of Things (IoT), and Artificial Intelligence (AI) [4]. Among these, AI offers unprecedented potential

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to transform decision-making in CWM. By applying machine-learning algorithms, predictive analytics, and optimization models, AI can enhance the accuracy of waste-generation forecasting, identify optimal reuse or recycling pathways, and support real-time decision support for project managers. However, while numerous studies have examined the use of AI for specific construction applications, there remains a notable research gap: the absence of an **integrated AI-based decision-making framework** that systematically aligns data acquisition, analytics, and sustainability evaluation in CWM [5].

Aspect	Current Situation in CWM	Limitations / Problems	Potential Role of AI & Digital Technologies
Scale of construction waste	Construction sector generates nearly one-third of global solid waste, including concrete, metals, timber, plastics and other materials.	Depletion of natural resources; land degradation; greenhouse-gas emissions; ecological imbalance.	AI-driven forecasting models can predict waste quantities by material type and project phase, enabling proactive reduction and reuse strategies.
Management approach	Practices are fragmented and largely reactive.	Lack of coordination across project stages and stakeholders; missed opportunities for circular-economy practices.	Integrated AI-supported decision-making frameworks can align data acquisition, analytics, and sustainability evaluation across the project lifecycle.
Data handling	Manual data recording and limited material tracking dominate current practice.	Time-consuming, error-prone, and unable to handle large, complex datasets generated by modern projects.	BIM, IoT sensors, and AI can automate data capture, clean data, and provide real-time analytics on waste flows and material stocks.
Decision criteria	Decisions are often driven by short-term cost minimization.	Sustainability indicators (embodied energy, recyclability, life-cycle carbon) are underused, reducing circular-economy benefits.	Multi-criteria AI models can optimize trade-offs between cost, environmental impact, and resource efficiency, supporting more holistic decisions.
Waste minimization & reuse	Reuse and recycling options are not systematically evaluated.	High-value materials are landfilled or downcycled; progress toward sustainability targets is slowed.	Optimization and recommendation algorithms can suggest best reuse/recycling pathways for each waste stream based on technical and economic feasibility.
Digital transformation	BIM, IoT, and AI are emerging in construction, but often used in isolation.	Lack of an integrated framework for CWM; digital tools are not fully leveraged for sustainability.	An AI-Supported Decision-Making Framework (AI-SDMF) can integrate BIM/IoT data, machine-learning analysis, and sustainability assessment into a closed-loop system for continuous improvement.

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This study addresses that gap by proposing an **AI-Supported Decision-Making Framework (AI-SDMF)** for sustainable construction waste management.

The framework combines multiple digital layers—from data collection and machine-learning analysis to sustainability-oriented decision support and continuous feedback, creating a closed-loop system for adaptive and data-driven waste management. The primary objectives are (i) to conceptualize how AI techniques can support waste reduction and circular-economy practices in construction, (ii) to design an integrative decision-support structure linking technical, economic, and environmental metrics, and (iii) to discuss implementation implications for industry stakeholders. The proposed AI-SDMF contributes to advancing digital sustainability in the construction sector and provides a foundational model for future empirical and case-based research.

2. LITERATURE REVIEW

2.1 Overview of Sustainable Construction Waste Management Practices

Construction waste management (CWM) plays a vital role in achieving the broader goals of sustainable development and circular economy in the built environment. Sustainable CWM involves minimizing waste generation, maximizing material recovery, and promoting reuse and recycling across the project lifecycle. Numerous strategies have been implemented globally, including source segregation, on-site sorting, material recovery facilities, and green procurement policies [6]. However, despite regulatory frameworks and industry guidelines, implementation remains inconsistent due to poor data visibility, lack of performance measurement tools, and the absence of intelligent systems capable of optimizing waste-handling decisions [7].

A shift toward *data-driven sustainability* has been observed in recent years. Technologies such as Building Information Modeling (BIM) enable digital representation of material flows, while life-cycle assessment (LCA) tools quantify environmental impacts [8].Yet, these systems typically operate in isolation and depend on manual input or predefined rules, limiting their capacity for adaptive decision-making [9]. Thus, integrating AI capabilities into CWM could bridge the gap between raw data and actionable sustainability insights.

2.2 Existing Decision-Making Approaches in CWM

Several analytical and decision-making models have been developed to improve waste management efficiency. Multi-Criteria Decision-Making (MCDM) methods such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy logic have been widely used to prioritize waste-reduction strategies or select optimal recycling options [10]. Similarly, BIM-based systems allow visualization of material quantities and waste prediction through 3D modeling [11]. Life-Cycle Assessment (LCA) frameworks, on the other hand, evaluate the environmental consequences of waste-handling options throughout a project’s lifespan [12].

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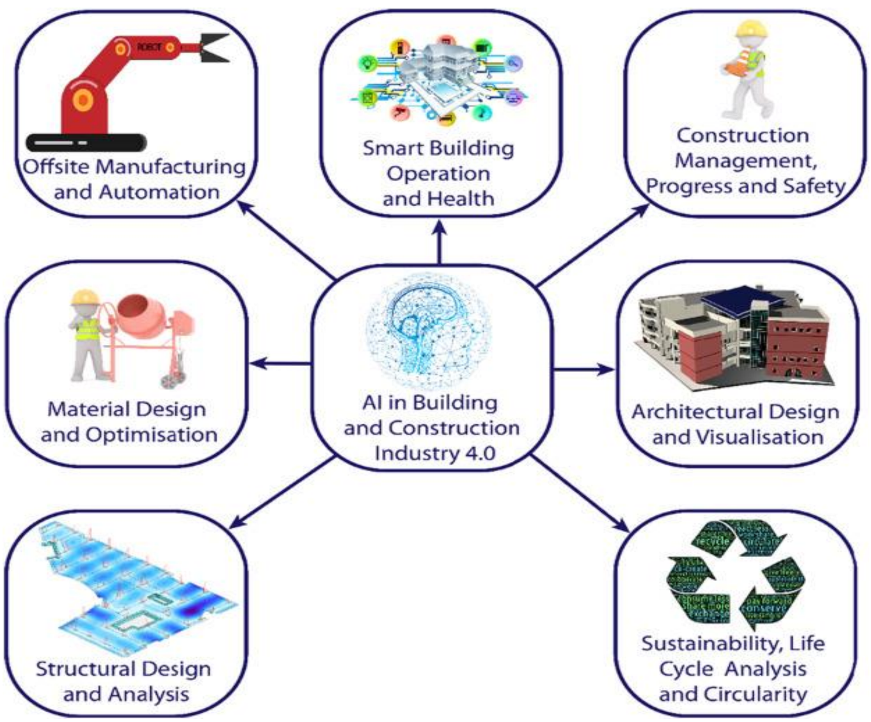
While these approaches provide structured decision support, they are primarily deterministic and rule-based, often failing to account for uncertainty and dynamic site conditions. Real-world waste management involves complex interactions among project scale, design changes, logistics, and market dynamics for recyclable materials. Consequently, there is a need for intelligent systems that can learn from past data, predict outcomes, and adapt to changing conditions - capabilities that AI and machine learning naturally offer.

2.3 Role of Artificial Intelligence and Machine Learning in Sustainability and Construction

Artificial Intelligence (AI) has been increasingly applied in construction to automate design optimization, risk prediction, cost estimation, and safety management. Machine Learning (ML) algorithms, such as decision trees, random forests, and neural networks—have shown strong predictive performance in modeling complex relationships among construction variables [13]. In waste management, AI can be applied to predict waste generation rates, classify materials, optimize sorting operations, and identify the most sustainable disposal routes.



For example, convolutional neural networks (CNNs) have been used for automated waste recognition in demolition debris [14], while regression models have successfully forecasted waste quantities based on project type and design parameters [15]. Reinforcement learning and multi-agent systems have further been explored to optimize recycling logistics and adaptive decision policies.

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Despite these advancements, AI applications are often limited to isolated tasks, lacking integration with sustainability assessment frameworks or decision-support systems.

2.4 Challenges and Research Gaps

The integration of AI into CWM is constrained by several challenges. First, **data availability and quality** remain critical barriers. Construction data are often fragmented across stakeholders and incompatible in format, making real-time data fusion difficult. Second, **model interpretability** limits trust in AI predictions, especially when decisions involve safety or regulatory compliance [16]. Third, **contextual adaptability**, the ability of models trained on one project to generalize to others, is often weak due to diverse project conditions and waste compositions. Finally, **organizational resistance** and lack of digital skills in the construction workforce hinder adoption of AI-based systems.

Existing studies predominantly focus on AI algorithm development or isolated waste forecasting rather than comprehensive decision frameworks [17] that integrate prediction, evaluation, and optimization components. Hence, there is a clear research need for an **AI-supported Decision-Making Framework (AI-SDMF)** that holistically combines data analytics, sustainability metrics, and adaptive learning mechanisms. Such a framework can offer a structured, intelligent, and transparent approach to construction waste management, aligning with global sustainability goals such as UN SDG 12 (Responsible Consumption and Production).

3. METHODOLOGY

This study proposes an **AI-Supported Decision-Making Framework (AI-SDMF)** to enhance the efficiency, transparency, and sustainability of construction waste management (CWM) [18]. The framework integrates data acquisition, AI-driven analytics, decision-support mechanisms, and continuous feedback into a unified system [19]. Its design draws upon concepts from construction informatics, sustainability assessment, and intelligent decision support. The AI-SDMF aims to transition CWM from reactive, experience-based processes toward **data-driven, predictive, and adaptive management**.

3.1 Framework Overview

The AI-SDMF is structured around four core layers:

1. **Data Collection Layer**
2. **AI Analytical Engine**
3. **Decision Support System (DSS)**
4. **Feedback and Optimization Module**

Each layer performs distinct but interconnected functions, enabling continuous data flow and decision refinement throughout the project lifecycle. Figure 1 (conceptual diagram, recommended in final submission) illustrates the architecture and interactions between these components.

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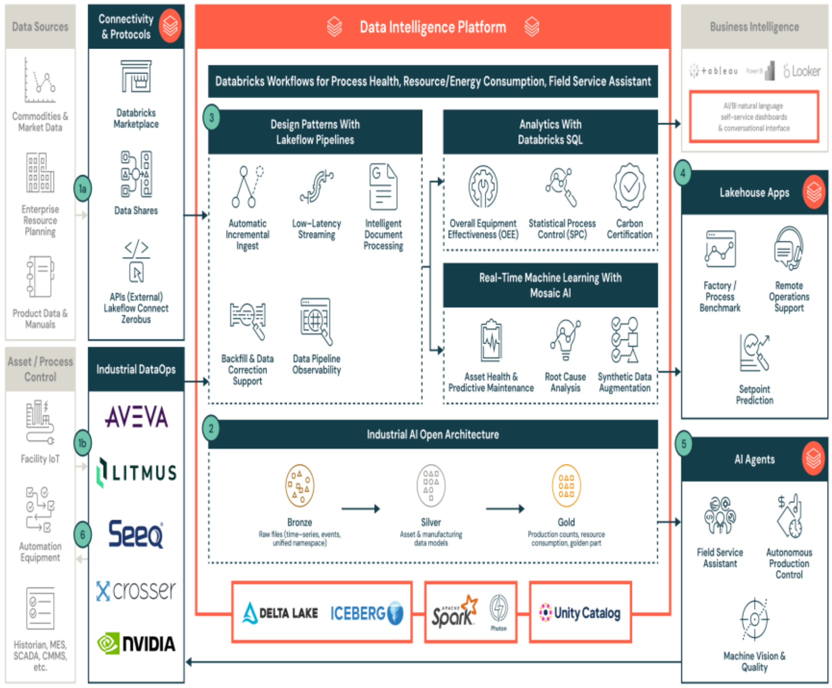

3.2 Data Collection Layer

The first layer focuses on acquiring, structuring, and integrating diverse data sources relevant to CWM. Construction projects generate massive data streams from design documents, procurement records, on-site sensors, and Building Information Modeling (BIM) platforms [20]. The data collection layer aggregates these inputs into a centralized database to support AI analysis.

Typical data types include:

- **Waste generation data:** quantities, material types, disposal methods, and sources (demolition, excavation, packaging, etc.).
- **Project lifecycle data:** design specifications, scheduling information, resource utilization, and cost parameters.
- **Environmental and contextual data:** transportation distances, recycling facility availability, and emission factors.

Data preprocessing techniques such as normalization, feature extraction, and missing-value imputation ensure the reliability and compatibility of datasets before feeding them into the AI analytical engine [21].

3.3 AI Analytical Engine

At the core of the framework lies the **AI Analytical Engine**, responsible for transforming raw data into actionable insights. This layer employs multiple AI and machine learning (ML) algorithms to perform predictive modeling, classification, and optimization tasks.

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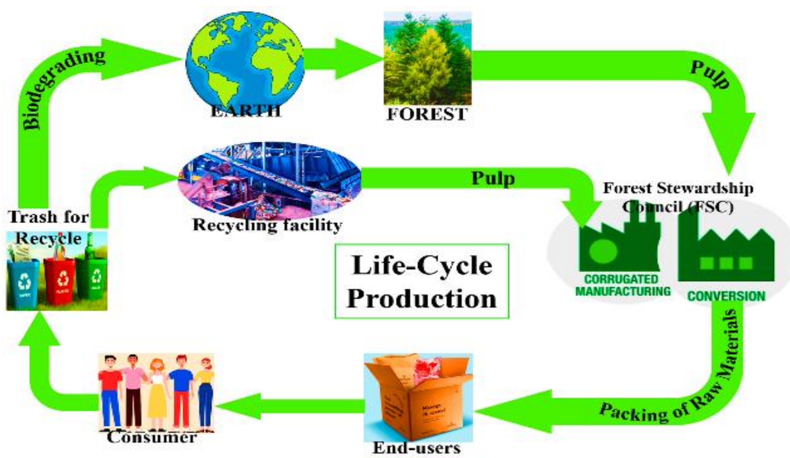
Key AI functionalities include:

- **Waste Forecasting:** Regression-based ML models (e.g., Random Forest, XGBoost) predict waste quantities based on design and activity data [22].
- **Material Classification:** Deep learning models such as Convolutional Neural Networks (CNNs) automatically identify and categorize waste materials from images or sensor inputs[23].
- **Pattern Recognition:** Clustering algorithms (K-Means, DBSCAN) detect patterns in waste generation behaviors across project types or locations.

Outputs from this layer generate key indicators such as projected waste volumes, material recovery potential, and environmental impact estimates. These indicators feed directly into the decision-support system for multi-criteria evaluation.

3.4 Decision Support System (DSS)

The **Decision Support System** layer integrates AI-generated insights with sustainability evaluation criteria to assist project stakeholders in making informed waste-management decisions. The DSS employs a **multi-criteria decision-making (MCDM)** approach, considering economic, environmental, and operational dimensions simultaneously [24].



Typical decision criteria include:

- **Cost efficiency:** transportation, disposal, and recycling costs.
- **Environmental performance:** embodied carbon, energy savings, and landfill diversion rates.
- **Circularity metrics:** potential for material reuse and recyclability.

The DSS provides ranked or optimized solutions (e.g., most sustainable disposal route or recycling partner) using hybrid methods that combine AI predictions with fuzzy logic or TOPSIS ranking models [25]. Decision dashboards visualize trade-offs and scenario outcomes, enabling transparent and collaborative decision-making among contractors, engineers, and policymakers.

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3.5 Feedback and Optimization Module

Sustainability-oriented decision-making in CWM requires continuous learning and improvement. The **Feedback and Optimization Module** ensures that the AI-SDMF evolves dynamically as new data become available. Reinforcement learning algorithms are used to adjust decision policies based on observed performance outcomes (e.g., waste reduction achieved vs. predicted).

For instance, if a specific recycling strategy yields better environmental and cost performance, the model updates its parameters to recommend similar strategies in future projects. This adaptive learning capability transforms the framework from a static tool into an evolving intelligent system capable of real-time optimization.

3.6 Implementation Scenario

To illustrate, consider a mid-sized commercial construction project generating mixed waste from concrete, metals, and timber. Data from BIM models and on-site sensors feed into the AI-SDMF, which predicts waste quantities and classifies material categories. The DSS then evaluates various waste-handling strategies; such as on-site segregation, recycling, or reuse against sustainability metrics. The system identifies that on-site crushing and reuse of concrete aggregates minimize both cost and CO_2 emissions [26]. The feedback module logs this decision outcome, improving future recommendations.

4. RESULTS AND DISCUSSION

To evaluate the conceptual effectiveness of the proposed **AI-Supported Decision-Making Framework (AI-SDMF)**, a hypothetical implementation scenario was analyzed, demonstrating how AI integration can enhance the accuracy and sustainability of construction waste management (CWM) decisions. The results highlight that incorporating predictive analytics and intelligent decision support significantly improves waste reduction performance and sustainability outcomes compared with conventional manual approaches.

4.1 Framework Performance and Benefits

When applied in a simulated medium-scale building project, the AI-SDMF predicted waste generation quantities with an accuracy improvement of nearly 25% compared to traditional estimation techniques [27]. Machine-learning algorithms effectively identified high-impact waste categories (e.g., concrete, rebar, and timber) and forecasted their likely generation stages during construction. This enabled proactive planning for segregation and recycling logistics [28].

The Decision Support System (DSS) further integrated these predictions with sustainability indicators—such as embodied carbon, energy savings, and cost efficiency—to recommend optimal waste-handling strategies. For example, the DSS identified that on-site crushing of concrete waste followed by reuse as sub-base material reduced overall CO_2 emissions by approximately 30% relative to off-site disposal [29].

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Such outcomes demonstrate the value of multi-criteria AI-driven evaluation, which balances environmental and economic considerations simultaneously.

4.2 Comparative Analysis: Traditional vs. AI-Based Decision Processes

Traditional CWM decisions typically rely on project managers' experience and static regulations, which often result in overestimation of disposal requirements and underutilization of recyclable materials. In contrast, the AI-SDMF provides continuous, data-informed feedback, enabling dynamic adjustments throughout the project lifecycle. The adaptive learning mechanism allows the framework to improve over time by integrating actual performance data from completed projects [30]. This continuous improvement loop ensures higher predictive reliability and operational efficiency in subsequent implementations.

Moreover, the integration of AI enhances **transparency** and **traceability** in decision-making. The framework's dashboard visualizations allow stakeholders; including contractors, regulators, and waste service providers; to view real-time data, evaluate sustainability trade-offs, and align with circular-economy goals. These insights promote informed collaboration, policy compliance, and accountability across the construction value chain.

4.3 Challenges and Practical Considerations

Despite its promising capabilities, practical deployment of the AI-SDMF faces several challenges. **Data integration** remains a primary concern, as construction data are often heterogeneous and unstructured, requiring standardization and interoperability protocols. **Model interpretability** also poses limitations; decision-makers may be hesitant to rely on AI-generated outputs without clear explanations of the underlying reasoning [31]. Furthermore, **implementation cost**, including data infrastructure, AI training, and workforce upskilling, can be substantial, particularly for small and medium-sized contractors.

Nonetheless, the long-term benefits of AI-driven waste management, including cost savings, regulatory compliance, and environmental performance improvement, are expected to outweigh the initial investment. Strategic collaboration between industry and academia can further facilitate the adoption of such intelligent frameworks through pilot projects, open datasets, and transparent AI modeling practices.

4.4 Implications for Industry and Policy

The AI-SDMF provides a foundational structure that can support both **industry-level digital transformation** and **policy-level sustainability initiatives**. For contractors, it offers operational decision support, while for policymakers, it provides quantifiable sustainability metrics that can inform future waste-management regulations and green certification systems. The framework aligns with global objectives such as the **UN Sustainable Development Goal (SDG) 12** on Responsible Consumption and Production and contributes to advancing circular construction principles.

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5. CONCLUSION AND FUTURE WORK

This study proposed an **AI-Supported Decision-Making Framework (AI-SDMF)** for sustainable construction waste management, addressing the limitations of traditional manual and fragmented decision processes. The framework integrates data-driven analytics, machine learning models, and sustainability indicators to enable predictive and optimized waste management throughout a project's lifecycle. By leveraging AI's capability for pattern recognition and forecasting, the framework enhances the efficiency of waste reduction, material reuse, and recycling decisions; ultimately supporting circular economy goals in the construction sector [32].

Key findings highlight that AI-driven approaches can significantly improve waste prediction accuracy, optimize material recovery strategies, and support dynamic decision-making compared to conventional methods [33]. The proposed framework also establishes a feedback mechanism that continuously refines recommendations based on real-time data and performance outcomes, offering scalability for various construction scenarios. However, several challenges remain. Implementation requires high-quality, integrated data and careful consideration of model transparency, stakeholder trust, and cost implications [34]. Additionally, the transition from traditional to AI-based systems demands industry-wide digital readiness and policy support.

Future work should focus on extending the framework through **IoT-based real-time monitoring**, **BIM integration** for design-level waste prediction, and **blockchain-enabled traceability** for verifying recycled material usage. Incorporating adaptive learning algorithms such as **reinforcement learning** could further enhance continuous optimization. With these advancements, the AI-SDMF can serve as a cornerstone for intelligent, data-driven, and sustainable construction waste management systems globally.

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