

An AI-Enabled Framework for Enhancing Sustainable Decision-Making in Engineering Project Management

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Abstract

Decision-making in sustainable engineering project management presents a complex, multi-objective challenge. Traditional methods are often reactive and struggle to balance conflicting economic, environmental, and social goals. Although Artificial Intelligence (AI) offers strong predictive capabilities, many existing decision-support approaches remain fragmented or operate as opaque “black-box” systems, limiting trust in high-stakes decisions. To address this gap, this paper develops a novel conceptual framework through a clarified, PRISMA-informed synthesis of 46 retained studies spanning five domains: AI in project management, sustainability and lifecycle assessment, multi-criteria decision-making, explainable AI, and enabling digital technologies. The framework’s key contribution is a multi-layered architecture that integrates predictive machine learning for forecasting lifecycle impacts, Multi-Criteria Decision-Making (MCDM) for trade-off analysis, and Explainable AI (XAI) to provide human-interpretable justifications for recommendations. As a result, the proposed architecture shifts decision-making from reactive assessment to proactive, transparent, and data-driven optimisation. As a conceptual contribution, the framework provides both a defensible reference model for practice and a platform for future prototype development and empirical validation.

Keywords: Artificial Intelligence (AI), Sustainable Decision-Making, Engineering Project Management, Explainable AI (XAI), Decision-Support Systems

1 Introduction

The imperative to embed sustainability into 21st-century engineering practice has become a defining challenge (Azapagic & Perdan, 2011), representing a core component of the broader transition toward sustainable construction within Industry 4.0 (Alawag et al., 2024b). This transition requires reconciling economic development with social and environmental responsibility, often framed through the “triple bottom line” and the United Nations Sustainable Development Goals (SDGs) (Adamantiadou & Tsironis, 2025; Ramos-Gavilán et al., 2024). Accordingly, engineering design, delivery, and project management now require more integrated and sustainability-oriented decision logics.

Engineering project management confronts this multi-objective challenge with processes that are often fragmented and reactive (Hameed et al., 2024). Traditional project management, whether classical or agile (Ciric et al., 2019), frequently prioritises the immediate and quantifiable metrics of cost and schedule, struggling to integrate complex, long-term sustainability trade-offs (Manzoor et al., 2021). Current tools fail to handle

predictive trade-offs effectively—such as “lifecycle cost versus long-term carbon, and material circularity versus up-front cost-effectiveness” —thereby perpetuating a significant practice gap.

Although the potential of AI to transform project management is increasingly recognised, its application remains fragmented (Manzoor et al., 2021). Many powerful AI solutions, particularly those involving complex predictive models, still operate as opaque “black-box” systems that do not provide the transparency required for high-stakes engineering decisions (Rahman et al., 2022). This lack of interpretability weakens trust, constrains auditability, and obscures potential bias, making meaningful human-AI collaboration difficult in early project phases and slowing adoption in high-risk engineering contexts (Abioye et al., 2021; Bidhendi & Azizi, 2021; Chinnaraju, 2025).

The solution lies not merely in applying AI, but in integrating predictive intelligence, structured trade-off analysis, and interpretability within one lifecycle-oriented workflow. Recent studies have demonstrated the value of data-driven feasibility assessment for sustainable smart-city infrastructure (Al-Azazi, 2026) and technology-enabled risk mitigation in smart construction (Al-Azazi et al., 2025), yet these contributions remain application-specific rather than architecturally unified. Likewise, prior work has successfully applied AI and machine learning to specific tasks such as Life Cycle Assessment (LCA) (Ghoroghi et al., 2022; Koyamparambath et al., 2022) and sustainable material selection (Wibowo, 2024), but such efforts are usually siloed. Motivated by this gap, the present study proposes a unified AI-enabled conceptual framework that integrates predictive analytics, MCDM, and XAI into a single decision-support architecture for sustainable engineering project management.

This paper proposes a holistic, multi-layered framework designed to shift sustainable project management from a reactive to a proactive paradigm. We first present a standalone literature review to synthesise the fragmented research streams that inform the study, then clarify the research method used to develop the framework. We subsequently describe the architecture in detail, demonstrate its practical use through an illustrative sustainable bridge scenario, and discuss its theoretical and practical implications, including future integration with Digital Twin technology (Seegrün et al., 2023). The novelty of this study lies in the theoretically grounded integration of predictive machine learning, Multi-Criteria Decision-Making (MCDM), and Explainable AI (XAI) within a single proactive framework for sustainable engineering project management. Unlike existing studies that address these components in isolation, the proposed architecture couples lifecycle-oriented sustainability assessment with transparent, AI-driven optimisation to support early-stage project decisions. This contribution provides both a conceptual roadmap for researchers and a practical reference model for practitioners seeking to operationalise trustworthy, AI-enabled decision-making in complex engineering contexts.

2 Literature Review and Research Gaps

2.1 Thematic Literature Synthesis

This literature review is presented as a standalone section because it constitutes the analytical foundation of the framework rather than a mere extension of the research design. The reviewed studies were used to identify recurring themes, conceptual anchors, and unresolved gaps in sustainable engineering project decision support. Accordingly, the review moves beyond description by organizing prior work into coherent knowledge streams and evaluating where integration remains insufficient.

2.2 Critical Gaps in Existing Research

The revised review corpus comprises 46 retained studies that collectively ground the framework. These studies were selected because they directly inform one or more elements of sustainable engineering decision support and are summarized in Appendix A. The synthesis revealed five core domains that repeatedly appear in the literature but are rarely integrated into one transparent decision-support architecture:

1. AI in engineering project management: studies addressing predictive analytics, project control, scheduling, uncertainty, and risk management in engineering and construction contexts (Bidhendi & Azizi, 2021; Hameed et al., 2024; Manzoor et al., 2021).
2. Sustainability assessment and lifecycle modelling: studies focused on LCA, environmental impact evaluation, material performance, carbon reduction, and circularity-oriented assessment (Ghoroghi et al., 2022; Koyamparambath et al., 2022; Yahia et al., 2024).
3. Multi-Criteria Decision-Making (MCDM) and optimisation: studies providing formal approaches for balancing cost, carbon, resilience, and social trade-offs in engineering decisions (Elmousalami et al., 2025; Yu et al., 2018; Zeng et al., 2007).
4. Explainable AI (XAI) and trustworthy analytics: studies concerned with interpretability, accountability, and the translation of model behaviour into defensible human reasoning (Chinnaraju, 2025; Rahman et al., 2022).
5. Enabling technologies and digital integration: studies on BIM, Digital Twins, blockchain, green supply chains, and other digital infrastructures that can feed or operationalize AI-enabled decision support (Bazel & Baarimah, 2023; Ekanayake et al., 2019; Jones, 2014; Seegrün et al., 2023).

2.3 Theoretical Foundations for Framework Design

The theoretical foundation of the proposed framework emerges from the intersection of decision science, sustainability assessment, and human-centred AI. Across the reviewed literature, a recurring pattern is evident: strong methods exist for predicting outcomes, ranking alternatives, or improving transparency, but these capabilities are usually developed in parallel rather than as a coherent decision architecture. This fragmentation is particularly problematic in early project phases, where stakeholders must simultaneously reason about lifecycle impacts, risk, value, and accountability. Sustainability assessment and Life Cycle Assessment (LCA) provide the backbone for lifecycle-oriented decision-making because they enable a cradle-to-grave view of environmental burdens (Cabot et al., 2009; Yahia et al., 2024). However, the literature also shows persistent limitations: LCA remains data-intensive, slow, and frequently retrospective, which weakens its usefulness for early-stage project design (Ghoroghi et al., 2022). Recent AI-enabled LCA studies improve predictive speed and data handling (Koyamparambath et al., 2022), yet they generally stop at estimation rather than linking environmental predictions to broader project-level choice architectures.

MCDM and optimisation literature provides the formal logic needed to reconcile conflicting sustainability criteria such as cost, carbon, resilience, and social impact. Methods such as AHP, TOPSIS, and related optimisation routines make trade-offs explicit and can support the search for Pareto-efficient alternatives (Elmousalami et al., 2025; Yu et al., 2018; Zeng et al., 2007). Nevertheless, prior studies typically treat these methods as standalone decision tools rather than embedding them inside a broader predictive and explainable AI pipeline, leaving a methodological gap between forecasting, optimisation, and trust. Research on complex project management, risk, and resilience further reinforces the need for a proactive and integrated architecture. Traditional project management approaches remain ill-equipped to handle the uncertainty, interdependence, and lifecycle consequences of contemporary engineering systems (Ciric et al., 2019; Dempsey et al., 2022). Although emerging work addresses AI-enabled risk forecasting and technology-mediated resilience (Aguda et al., 2021; de Melo et al., 2024; Zhang et al., 2025), the literature still lacks a single framework that couples predictive analytics, structured trade-off logic, lifecycle sustainability, and interpretability in a way that supports accountable human decision-making.

3 Research Method

3.1 Research Design and Framework Development Procedure

- Define inputs (Layer 1): First, the study identifies the heterogeneous data inputs required for a holistic assessment, including parametric BIM data, LCA inventories, risk and constraint data, and stakeholder or policy requirements.

- Build the processing core (Layer 2): Second, the analytical engine is specified to combine predictive modelling for lifecycle performance with optimisation logic capable of navigating trade-offs among competing sustainability objectives.
- Integrate transparency (Layer 3): Third, an Explainable AI (XAI) layer is embedded to translate model outputs into human-interpretable explanations, thereby addressing the black-box problem and strengthening accountability.
- Design outputs (Layer 4): Finally, the framework is operationalised through an interactive decision-support interface that communicates key indicators, trade-off patterns, and AI-generated justifications to human decision-makers.

3.2 Search Strategy, Eligibility Criteria, and Gap Analysis

For this revision, the review protocol was clarified using a PRISMA-informed, purposive screening logic. Searches were oriented around combinations of terms related to AI or machine learning, sustainable engineering, project management, lifecycle assessment, multi-criteria decision-making, explainable AI, BIM, and Digital Twins. Studies were retained when they were peer-reviewed and directly relevant to sustainable engineering project management or to a supporting analytical component of the proposed architecture; older studies were retained only when they provided foundational theoretical grounding. The final retained corpus comprises 46 studies, all identified in Appendix A. These studies were then thematically coded to expose recurring gaps, especially fragmentation among predictive modelling, decision optimisation, lifecycle assessment, and interpretability.

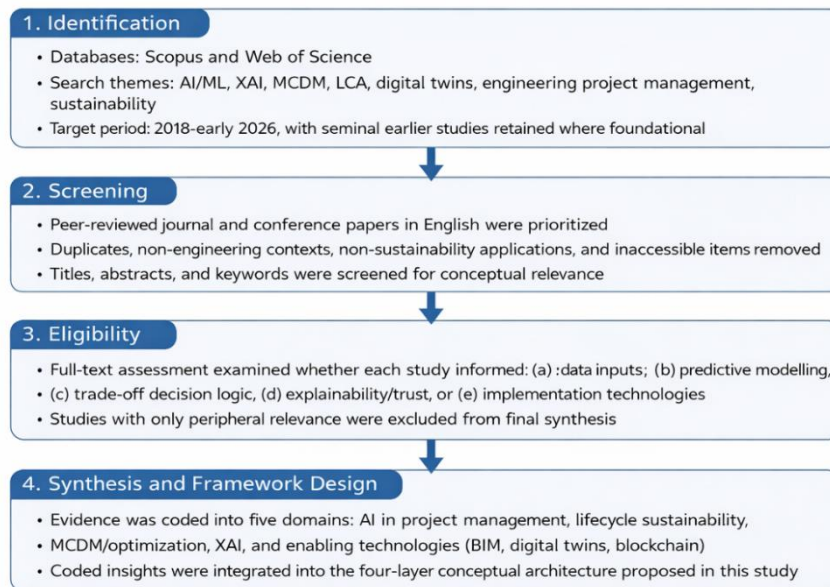


Figure 1. PRISMA-inspired literature screening and framework synthesis workflow

The procedure in Fig. 1A clarifies how the retained studies were screened, coded, and translated into the final framework, thereby making the review logic and gap-identification pathway more explicit and replicable.

4 Results and Discussion

4.1 Results: The Proposed AI-Enabled Framework

Design Principles and Architecture: The framework is based on four design principles intended to overcome limitations in current approaches: proactivity, transparency, modularity, and user-centricity. Together, these principles reposition sustainable decision support from end-stage evaluation toward early, iterative, and explainable analysis. These principles are translated into a multi-layered architecture, as depicted in Fig. 2. The framework comprises four interconnected layers that process information from raw, heterogeneous project data to actionable recommendations and explanation-ready outputs. Operationally, data move from harmonised inputs to predictive inference, then to multi-objective optimisation, then to XAI-based interpretation, and finally to dashboard-based decision support. Importantly, the information flow is iterative rather than strictly linear: changes in stakeholder priorities or constraint values can be fed back into the predictive and optimisation layers to update the recommended solution set.

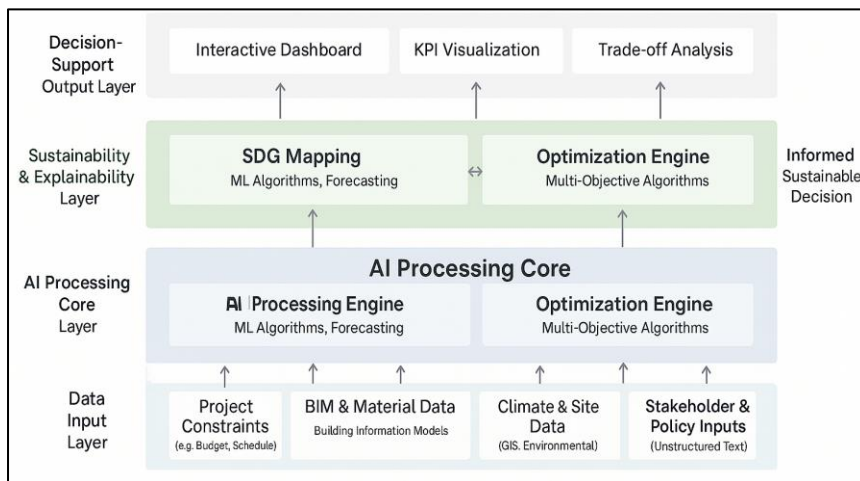


Figure 2. Architecture of the AI-enabled sustainable decision-making framework

Layer 1: Data Input Layer: This foundational layer serves as the data aggregation hub, ingesting and harmonising heterogeneous, multi-format data that defines the project context. It is designed to integrate:

- **Project Constraints:** Budget, schedule, and stakeholder/policy inputs. This includes regulatory requirements and sustainability reporting goals (Karbekova et al., 2023) that define the boundaries of the decision-making problem.
- **BIM & Material Data:** Building Information Models (BIM) provide detailed geometric and material data. This layer leverages BIM as a central data source for quantity take-offs and spatial coordination (Ashraf, 2024; Ekanayake et al., 2019). This aligns with Integrated Project Delivery (IPD) principles, where shared, high-quality data is essential for collaboration (Jones, 2014). Furthermore, BIM data is a critical input for modelling the building's energy performance, a key sustainability metric (Alkhatib et al., 2021).
- **Sustainability & Lifecycle Data:** This includes material properties and Life Cycle Assessment (LCA) inventories (Cabot et al., 2009; Ghoroghi et al., 2022; Koyamparambath et al., 2022), and green supply chain management (GSCM) data (Musarat et al., 2022).
- **Climate & Site Data:** This component integrates geospatial information systems (GIS), climate models, and site-specific risk data (de Melo et al., 2024). It also accommodates safety-related data streams and smart emergency detection requirements that may influence sustainability, resilience, and operational performance (Ammad et al., 2020; Kasim et al., 2025).

Layer 2: AI Processing Core: This is the analytical engine of the framework, comprising two primary modules:

- **The Predictive Engine:** This module utilises machine learning algorithms (e.g., regression, forecasting) to analyse the integrated data from Layer 1 and predict the future performance of project alternatives. It forecasts outcomes such as lifecycle carbon emissions (Koyamparambath et al., 2022), operational energy consumption, project delays, and potential risks (Zhang et al., 2025). A key function is predictive maintenance and lifecycle cost modelling, allowing the framework to forecast long-term operational costs rather than just initial capital costs (Almuammari et al., 2025; Jariwala, 2024). This engine can also be specialised for complex engineering predictions, such as forecasting wind loads on sustainable tall building designs (Alkhatib et al., 2024).
- **The Optimisation Engine:** This module employs algorithms to navigate the complex trade-offs between these predicted outcomes. It systematically explores the solution space to identify a set of Pareto-optimal solutions that represent the best possible compromises. This is achieved by integrating Multi-Criteria Decision-Making (MCDM) methodologies (e.g., AHP, TOPSIS) (Elmousalami et al., 2025; Yu et al., 2018) with optimisation algorithms, such as the Genetic Algorithms (Zeng et al., 2007) mentioned in the original framework design.

Layer 3: Sustainability & Explainability Layer: This layer translates the raw outputs of the AI Core into a meaningful and trustworthy context.

- **SDG Mapping:** This component links the predicted KPIs to the broader framework of the UN Sustainable Development Goals (SDGs), providing a globally recognised context for the project's sustainability performance. This ensures the engineering solution is aligned with global sustainability and social impact targets (Adamantiadou & Tsironis, 2025).
- **The XAI Engine:** This is the framework's most critical component for building trust. It uses post-hoc explanation techniques like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) to analyse the AI models from Layer 2 (Chinnaraju, 2025). This engine generates human-readable justifications (e.g., "Design A is 15% more expensive but 40% more resilient due to material choice X") that clarify why the AI recommends a certain option, thereby ensuring decision transparency and accountability (Rahman et al., 2022).

Layer 4: Decision-Support Output Layer: This is the user-facing interface that presents the processed information to human project stakeholders. An interactive decision-support dashboard visualises KPIs, sustainability metrics, and the Pareto front of optimal solutions. Crucially, it displays the XAI-generated "justification reports" alongside the recommendations, empowering defensible, informed, and holistic decisions.

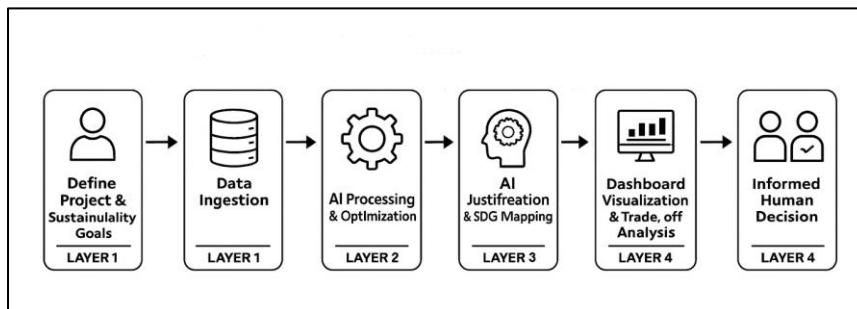


Figure 3. Operational workflow of the AI-enabled framework

4.2 Discussion: Illustrative Application and Implications

Conceptual Application: A Sustainable Bridge Design Scenario. To illustrate the framework's functionality, consider a municipal authority evaluating alternative bridge concepts under simultaneous economic, environmental, and resilience-oriented objectives. In the revised scenario, the decision problem is defined not only by material choice, but also by deck configuration, expected maintenance interval, corrosion exposure class, flood return-period risk, traffic disruption cost during repairs, embodied carbon, and community service continuity over a 50-year analysis horizon. These added parameters make the hypothetical case more representative of real engineering decision environments, where lifecycle consequences and stakeholder trade-offs must be examined together rather than sequentially. In a traditional approach, the decision is often governed by the lowest initial capital cost, likely favouring a standard steel girder design. The AI-enabled framework transforms this logic by explicitly exposing lifecycle consequences and the reasons behind alternative rankings:

1. **Data input (Layer 1):** The framework ingests BIM models for multiple design options (e.g., steel girder and advanced composite), alongside material-specific LCA data (Wibowo, 2024; Yahia et al., 2024), long-term maintenance cost assumptions (Jariwala, 2024), hazard and climate exposure parameters, and service-disruption variables relevant to bridge closures.
2. **AI processing (Layer 2):** The predictive engine forecasts lifecycle cost, embodied and operational carbon, maintenance frequency, delay risk, and resilience indicators. The optimisation engine then searches across these predicted outputs to generate a Pareto-efficient set of alternatives that makes trade-offs explicit rather than implicit (Fig. 4).
3. **Explainability (Layer 3):** Suppose the optimal set includes an advanced composite option with a higher upfront cost. Rather than presenting this as an opaque recommendation, the XAI engine produces a human-readable justification such as: the composite option increases initial cost by 15-16%, but reduces lifecycle maintenance expenditure, corrosion-related disruption, and climate-vulnerability exposure enough to lower total ownership cost over the analysis horizon (Chinnaraju, 2025).
4. **Decision support (Layer 4):** The stakeholder dashboard visualises these trade-offs (Table 1) and enables decision-makers to adjust weighting assumptions, compare near-optimal alternatives, and document the rationale for a final defensible selection.

Although the bridge example is used for exposition, the same logic can be transferred to vertical building retrofits, smart-building component choices, and infrastructure energy systems. For example, the framework could evaluate tall-building envelope alternatives under wind and energy criteria (Alkhatib et al., 2024) or assess the feasibility of energy-harvesting infrastructure options within smart-city programmes (Al-Azazi, 2026).

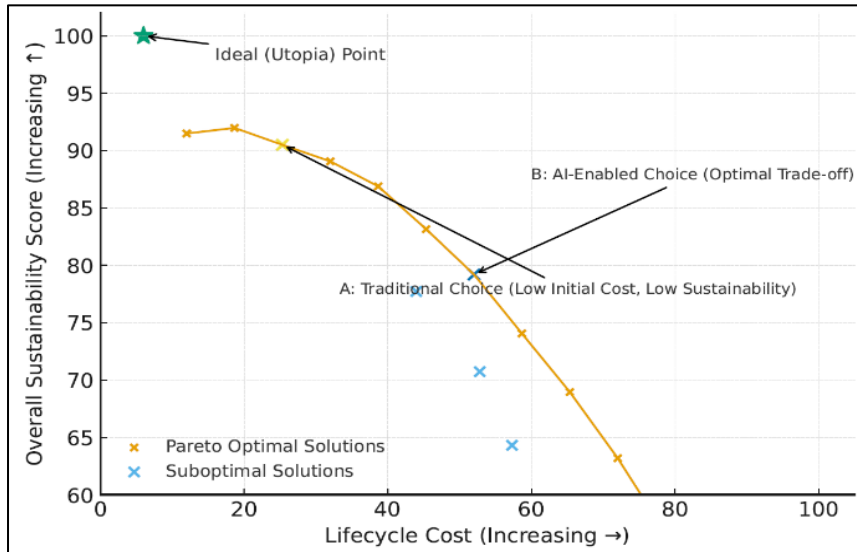


Figure 4. Illustrative Pareto front for bridge design trade-offs

Table 1. Hypothetical comparison of decision outcomes for bridge design

Metric	Traditional Cost-Focused Choice (Steel Girder)	AI-Enabled Holistic Choice (Advanced Composite)	Justification Provided by XAI
Initial Capital Cost	\$50 Million (Lowest)	\$58 Million (+16%)	Higher upfront costs are due to advanced material manufacturing.
Predicted Lifecycle Cost (50 Yrs)	\$85 Million	\$68 Million (- 20%)	Reduced need for repainting and corrosion repair (Nabeel, 2024).
Lifecycle Carbon Footprint (LCA)	120,000 tons CO ₂ -eq	75,000 tons CO ₂ - eq (-37.5%)	Lighter materials reduce transportation emissions; lower maintenance reduces energy use.
Climate Resilience Score	6.5 / 10	9.2 / 10 (+41.5%)	Higher resistance to corrosion from humidity and flooding is projected for the region (Al-Azazi et al., 2025).

Discussion of Implications: The proposed framework carries significant implications for both theory and practice in sustainable engineering and project management. Theoretically, it advances human-AI collaboration by operationalising proactive lifecycle thinking and by placing trustworthy AI at the centre of decision support rather than at the margins (Chinnaraju, 2025). Practically, it offers more defensible decision-making, stronger alignment with sustainability policy targets (Adamantiadou & Tsironis, 2025), improved long-term value, and clearer stakeholder communication. The contrast with traditional project management is especially important: conventional workflows are often linear, reactive, and dominated by initial-cost logic, whereas the proposed framework is iterative, predictive, and explicitly lifecycle-oriented. Figure 5 visualises this shift by comparing the traditional and AI-enabled decision pathways.

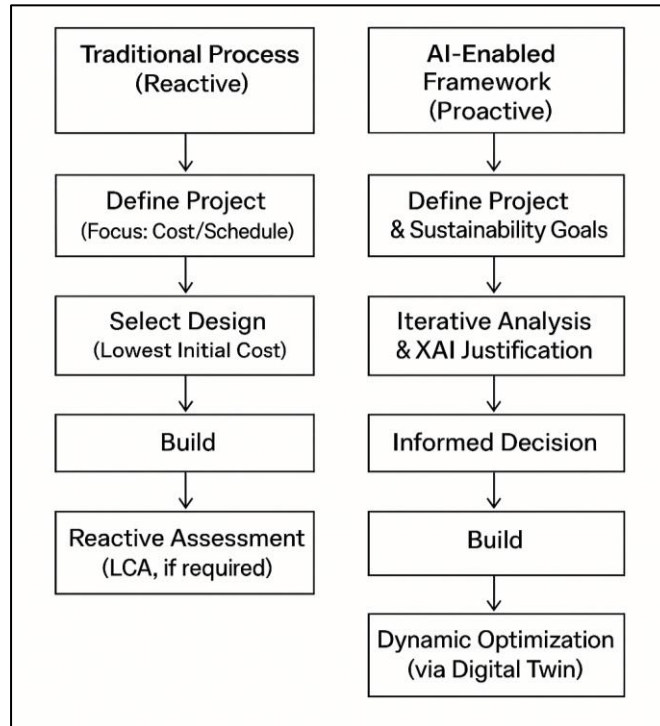


Figure 5. Comparative analysis: traditional vs. AI-enabled decision process

4.3 Framework Components and Enhanced Analysis

To elucidate the practical functionality, Table 2 (expanded from the original) connects sustainability criteria with the enabling AI techniques and supporting literature.

Table 2. Mapping between Sustainability Criteria and AI Techniques

Sustainability Criterion	Key Question for Decision-Maker	Enabling AI Technique	Example Application & Supporting Literature
Carbon Footprint (Planet)	Which design choice minimises lifetime emissions?	Regression Models, Time-Series Forecasting	“Predicting CO ₂ emissions based on material choices and operational energy models” (Ghoroghi et al., 2022; Koyamparambath et al., 2022).
Project Resilience (Planet/Profit)	How will the project withstand climate shocks?	Reinforcement Learning, Simulation	“Optimising structural design and material selection to enhance resistance against future flood or heatwave scenarios” (Aguda et al., 2021; Zhang et al., 2025).
Social Impact (People)	How will this affect the local community?	NLP Sentiment Analysis, Network Analysis	“Analysing community feedback from public forums... to gauge stakeholder satisfaction”, and aligning outcomes with UN SDGs (Adamantiadou & Tsironis, 2025; Hasas et al., 2024).
Economic Viability (Profit)	What is the lifecycle cost of this decision?	Predictive Analytics (Cost Modelling)	“Forecasting long-term operational and maintenance costs associated with different design and material options” (Almuammari et al., 2025; Jariwala, 2024).

To further solidify the critical role of Layer 3, Table 3 provides a comparison of the key XAI techniques that enable the framework's transparency (Chinnaraju, 2025).

Table 3. Comparison of key explainable AI (XAI) techniques for engineering decision support

Technique	Type	Application in Framework (Layer 3)	Strengths	Limitations in Engineering Context
LIME (Local Interpretable Model-Agnostic Explanations)	Local, Model-Agnostic	Explains individual predictions (e.g., “Why is this specific design recommended?”).	Easy to implement and understand; good for justifying a single decision to a stakeholder.	Can be unstable; explanations may vary. May oversimplify complex non-linear material behaviours (Chinnaraju, 2025).
SHAP (SHapley Additive exPlanations)	Local & Global, Model-Agnostic	Provides detailed feature importance for both individual decisions and the overall model.	Theoretically sound (game theory-based); provides consistent and accurate feature attributions.	Computationally intensive, which can be a bottleneck in complex, multi-variable project models (Chinnaraju, 2025).
Grad-CAM (Gradient-weighted Class Activation Mapping)	Local, Model-Specific	(Future Work) Visualising “hotspots” in BIM models or site data that led to a risk prediction.	Excellent for visual data (e.g., identifying potential flaws in a design image).	Primarily for CNNs; less applicable to the framework's current focus on tabular/numeric data (Chinnaraju, 2025).

4.4 Challenges and Limitations

Despite its promise, the framework faces several substantive challenges and limitations in practice. First is the issue of data dependency. The adage “garbage in, garbage out” applies: forecasting quality depends on access to reliable, well-structured, and interoperable data, yet construction data remain fragmented across organisations and project stages (Bidhendi & Azizi, 2021; Alawag et al., 2024a). Second, the framework entails non-trivial computational demands. Executing predictive models, multi-objective optimisation routines, and especially XAI methods such as SHAP can be resource-intensive, which may create adoption barriers for small and medium-sized engineering firms (Chinnaraju, 2025). A phased implementation strategy using modular cloud services, reduced-order models, or simplified indicator sets may therefore be necessary during early adoption. Third, and most importantly, there is an ethical and governance-related need for human oversight. The framework is intended to support decisions, not make them autonomously. Automation bias remains a real risk if users accept recommendations uncritically. Final accountability must remain with qualified human experts who can interpret context, scrutinize assumptions, and justify the chosen option. Finally, the present study remains conceptual and has not yet been empirically validated through prototype deployment or case-based testing.

5 Conclusion and Future Work

5.1 Conclusion

In conclusion, this paper addresses a critical gap in sustainable engineering by introducing a novel AI-enabled conceptual framework for improving sustainable decision-making in project management. The current landscape of decision-support tools remains reactive, fragmented, and frequently opaque, limiting their usefulness for complex, high-stakes engineering choices. By contrast, the proposed framework offers a proactive and transparent architecture that integrates lifecycle thinking, predictive analytics, multi-criteria trade-off logic, and explainable AI within one coherent decision-support workflow. The main contribution of this

research lies in the theoretically grounded integration of Multi-Criteria Decision-Making (MCDM), predictive AI, and Explainable AI (XAI). Together, these components provide a structured basis for balancing conflicting sustainability objectives while preserving human accountability and interpretability. As a conceptual contribution, the framework is intended to guide future prototype development, case-based validation, and operational integration with digital engineering environments such as BIM and Digital Twins. Ultimately, it provides a practical pathway toward more trustworthy, defensible, and lifecycle-aware engineering decisions.

5.2 Future Work

To further develop this conceptual framework, future investigations will follow three main tracks:

1. **Prototype Development and Simulation:** The first step is to develop a prototype of the decision-support system. This will involve “a simulation model to quantitatively test the framework” and validate its decision-optimisation algorithms (e.g., the MCDM and Genetic Algorithm components) in an experimental, controlled setting.
2. **Empirical Validation:** Following the simulation, the framework must be validated through “application in a real-world case study with an engineering firm”. This will be crucial to “evaluate the framework’s applicability and effectiveness in a live project setting”, assessing its impact on actual project outcomes, stakeholder trust, and the quality of sustainable decisions.
3. **Integration with Digital-Twin Technology:** The most significant avenue for future work is the “integration of the framework with Digital-Twin technology”. This was a brief point in the original paper, but supporting literature reveals this as a critical next step (Seegrün et al., 2023). We propose that this AI framework should serve as the “intelligent brain” for a project’s Digital Twin. The Digital Twin would provide the real-time, dynamic data from the physical asset (e.g., sensor data from a bridge under construction, real-time material usage from BIM updates) directly into the framework’s Data Input Layer (Layer 1). The framework’s AI Processing Core (Layer 2) would then perform continuous predictive analysis, and the Explainability Layer (Layer 3) would provide transparent justifications for any deviations or recommended interventions. This integration would create a dynamic and sustainable product lifecycle management system, enabling real-time optimization and adaptive decision-making far beyond the initial design phase (Seegrün et al., 2023).

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Declaration of Conflicting Interests

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Author Contribution

Abdullateef Ali: Conceptualisation, Methodology, Software, Writing – Original Draft. Saleem Ahmed Al-Azazi: Data Curation, Investigation, Writing – Original Draft. Aawag Mohsen Alawag: Supervision, Writing – Review & Editing. Amin Saif: Validation, Visualisation, Writing – Review & Editing. Farag Qasem: Resources, Investigation. All authors have reviewed and approved the final version of the manuscript for publication.

Declaration of Conflicting Interests

All authors declare that they have no conflicts of interest.

Declaration of Generative AI in The Writing Process

Not Applicable.

Data Availability/Supplementary Materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Statement

The authors declare that this research did not involve human or animal subjects.

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Appendix A. Retained Literature Corpus Used to Develop the Framework

The revised review corpus comprises 46 retained studies. Appendix A lists the studies with their full titles and analytical domains to improve transparency, traceability, and readability in the final revised manuscript.

Table A1. Retained literature corpus used in the framework synthesis

No.	Study	Condensed topical focus	Domain
1	Adamantiadou & Tsironis (2025)	Review of AI uses, implementation challenges, and future directions in project management	AI in project management
2	Aguda et al. (2021)	Decision-support opportunities and unresolved challenges in project delivery	MCDM/Decision support
3	Abioye et al. (2021)	Current capabilities, opportunities, and adoption barriers for AI in construction	AI in project management
4	Al-Azazi et al. (2025)	Emerging-technology strategies for reducing smart-construction risk	Sustainability/LCA
5	Al-Azazi (2026)	Data-driven feasibility assessment for piezoelectric harvesting in smart-city infrastructure	Sustainability/LCA
6	Alawag et al. (2024a)	State-of-the-art review of AI uptake, barriers, and risks in smart construction	AI in project management
7	Alawag et al. (2024b)	Industry 4.0 practices supporting quality management in sustainable construction	Sustainability/LCA
8	Alkhatib et al. (2021)	Review of BIM contributions to building energy-performance evaluation	Enabling technologies
9	Alkhatib et al. (2024)	Conceptual approach to wind-load design in sustainable irregular tall buildings	Sustainability/LCA
10	Alkhorasani & Alawag (2025)	AI applications for reverse-logistics return prediction	Enabling technologies
11	Almuammari et al. (2025)	Digital supply networks and public-private partnerships for socio-economic sustainability	Sustainability/LCA
12	Ammad et al. (2020)	Assessment of safety attributes in infrastructure projects	AI in project management
13	Ashraf (2024)	AI-enabled monitoring and compliance for climate-management challenges in oil and gas	Enabling technologies
14	Azapagic & Perdan (2011)	Engineering-oriented case studies on applied sustainable development	Sustainability/LCA
15	Bangalore Ramu et al. (2025)	Circular-resource reuse using sand-rubber tire mixtures in geotechnical engineering	AI in project management
16	Bazel & Baarimah (2023)	Bibliometric overview of blockchain adoption and trends in construction	Enabling technologies
17	Bidhendi & Azizi (2021)	Machine-learning applications in project management practice	AI in project management
18	Cabot et al. (2009)	Modelling strategy for embedding sustainability into decision processes	Sustainability/LCA
19	Chinnaraju (2025)	Conceptual foundation for interpretable and trustworthy AI decision-making	XAI
20	Ciric et al. (2019)	Comparison between agile and conventional project management approaches	AI in project management
21	Dahmus (2014)	Historical analysis of whether efficiency gains reduce resource consumption	AI in project management
22	de Melo et al. (2024)	Role of life-cycle assessment in geotechnical engineering practice	Sustainability/LCA
23	Dempsey et al. (2022)	Major barriers affecting success in conventional project management	AI in project management
24	Ekanayake et al. (2019)	Construction project-management challenges in a Sri Lankan case context	AI in project management
25	Elmoussalami et al. (2025)	Automation-oriented AI methods for sustainable construction management	Sustainability/LCA
26	Ghoroghi et al. (2022)	Machine-learning applications across life-cycle assessment workflows	Sustainability/LCA
27	Hameed et al. (2024)	AI contributions to construction project-management efficiency and sustainability	Sustainability/LCA
28	Hasas et al. (2024)	AI-enabled approaches for community development and social good	AI in project management
29	Jariwala (2024)	Integration of AI into sustainability-oriented project management practice	Sustainability/LCA
30	Jones (2014)	Integrated project delivery as a pathway to sustainable design and construction	Sustainability/LCA
31	Karbekova et al. (2023)	Dataset- and AI-driven sustainability reporting within Industry 4.0 quality management	Sustainability/LCA

No.	Study	Condensed topical focus	Domain
32	Kasim et al. (2025)	Requirements for Industry 4.0 adoption in smart emergency detection for construction	Enabling technologies
33	Koyamparambath et al. (2022)	AI-based prediction of environmental impacts from construction products	Sustainability/LCA
34	Manzoor et al. (2021)	Systematic review of AI in civil engineering for sustainable development	Sustainability/LCA
35	McIsaac & Morey (1998)	Cultural dimensions of engineers' roles in sustainable development	Sustainability/LCA
36	Musarat et al. (2022)	Review of green-construction supply-chain management practices	Enabling technologies
37	Nabeel (2024)	Big-data-driven resource allocation and risk mitigation in complex projects	MCDM/Decision support
38	Rahman et al. (2022)	Systematic review of AI-based life-cycle engineering in industrial production	Sustainability/LCA
39	Rajesh (2023)	Grey-model prediction of firms' environmental sustainability performance	Sustainability/LCA
40	Ramos-Gavilan et al. (2024)	Awareness-building on engineering's contribution to sustainable development	Sustainability/LCA
41	Seegrun et al. (2023)	Digital twins for sustainable product lifecycle management	Sustainability/LCA
42	Wibowo (2024)	AI assistants for building-material selection decisions	Sustainability/LCA
43	Yahia et al. (2024)	Sustainable material selection in building design and construction	Sustainability/LCA
44	Yu et al. (2018)	Sustainable planning perspective for construction-engineering projects	Sustainability/LCA
45	Zeng et al. (2007)	Fuzzy decision methodology for construction-project risk assessment	MCDM/Decision support
46	Zhang et al. (2025)	Economic-environmental trade-offs examined through process systems engineering	Sustainability/LCA