

Article

AI-Driven Process Mining for ESG Risk Assessment in Sustainable Management

Riccardo Censi ^{1,*}, Paola Campana ¹, Francesco Bellini ¹, Fulvio Schettino ² and Chiara De Pucchio ²

¹ Department of Management, Sapienza University of Rome, 00161 Rome, Italy; paola.campana@uniroma1.it (P.C.); francesco.bellini@uniroma1.it (F.B.)

² Department of Computer, Control, and Management Engineering, Sapienza University of Rome, Via Ariosto, 00185 Rome, Italy; fulvio.schettino@uniroma1.it (F.S.); depucchio.1838329@studenti.uniroma1.it (C.D.P.)

* Correspondence: riccardo.censi@uniroma1.it

Abstract

The construction sector faces growing challenges in integrating sustainability, risk management, and regulatory compliance, in line with initiatives such as the European Green Deal, the Corporate Sustainability Reporting Directive, and international building standards. However, the systematic adoption of ESG metrics in decision-making remains limited due to fragmented data, the lack of predictive tools, and reliance on static reporting. This study proposes and illustrates a digital framework, based on simulated data, that combines Artificial Intelligence, Process Mining, and Robotic Process Automation to enhance ESG risk assessment in sustainable construction management. The model, formalized through Business Process Model and Notation, integrates Machine Learning for risk weighting and classification, and leverages Web Scraping and Business Intelligence for dynamic data acquisition. A simulated case study involving 100 synthetic construction projects is used to demonstrate the internal logic and quantitative feasibility of the framework, showing how automated data integration and predictive modeling can improve the consistency of ESG risk identification and classification. While the results are illustrative rather than empirical, they confirm the analytical coherence and reproducibility of the proposed workflow. From a scientific perspective, it contributes an integrated methodology that bridges predictive analytics and process management for ESG evaluation. From a practical standpoint, it offers a structured and reproducible workflow to anticipate, classify, and mitigate ESG risks, supporting the construction sector's transition toward data-driven and sustainability-first management practices.

Keywords: artificial intelligence; ESG; process mining; construction management; risk assessment; sustainable construction management



Academic Editors: David Arditì,
Phuong Hoang Dat Nguyen,
Minsoo Baek and Md Nazmus Sakib

Received: 9 October 2025

Revised: 13 November 2025

Accepted: 20 November 2025

Published: 25 November 2025

Citation: Censi, R.; Campana, P.; Bellini, F.; Schettino, F.; De Pucchio, C. AI-Driven Process Mining for ESG Risk Assessment in Sustainable Management. *Buildings* **2025**, *15*, 4260. <https://doi.org/10.3390/buildings15234260>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The construction sector is undergoing a critical transition toward sustainability, resilience, and digitalization. Increasing urbanization, evolving environmental and social regulations, and the need to reduce the ecological footprint of production activities are reshaping project and organizational management paradigms [1]. Construction activities generate considerable environmental and social impacts that influence not only firms' competitiveness but also safety conditions, operational efficiency, and the overall quality of building processes [2].

Table 1 summarizes the main ESG (Environmental, Social, and Governance) impact areas in the construction sector, providing indicative quantitative reference values and a single-source mapping to support comparability and traceability across processes.

Table 1. ESG impact hotspots in the construction sector, with indicative quantitative ranges and units. Author’s elaboration based on sources [3–9].

ESG Area	Impactful Activity	Main Impact	Example Quantitative Range/Unit	Source
Environmental	Production and use of carbon-intensive materials (cement, steel)	High CO ₂ emissions and embodied energy in materials	Cement $\approx 0.85\text{--}0.95 \text{ kg CO}_2 \text{ kg}^{-1}$; Steel $\approx 1.8\text{--}2.0 \text{ kg CO}_2 \text{ kg}^{-1}$	[3]
	Water consumption and inefficient resource management	Water stress, ecosystem degradation	$0.3\text{--}0.5 \text{ m}^3 \text{ water m}^{-2} \text{ built area}$	[4]
	Construction and demolition waste management	Pollution, reduced circularity, landfill overload	$1.0\text{--}1.5 \text{ t waste per } 100 \text{ m}^2 \text{ floor area}$	[5]
Social	Working conditions on construction sites	Occupational safety and health	$2.5\text{--}3.0 \text{ recordable incidents per } 10,000 \text{ work hours}$	[6]
	Relations with local communities	Social acceptance, conflict mitigation	$>70\%$ of projects include community engagement plans	[7]
Governance	Supply chain management and due diligence	Reputational and compliance risks	$60\text{--}80\%$ of suppliers audited for ESG compliance in leading firms	[8]
	Transparency and non-financial reporting	Credibility with investors and stakeholders	$\approx 75\%$ of ENR-listed firms publish annual sustainability reports	[9]

Climate change, the growing scarcity of resources, and rising operational costs are increasingly influencing the stability of construction activities, the competitiveness of firms, and the sector’s overall ability to guarantee safety, efficiency, and quality standards [10]. On the policy side, initiatives such as the United Nations 2030 Agenda, the European Green Deal, and the Corporate Sustainability Reporting Directive have strengthened the role of environmental and social sustainability within institutional and industrial agendas. These programs encourage construction companies to use more advanced tools to measure, report, and manage sustainability performance [11,12]. Within this framework, ESG standards represent a key reference that guides organizations toward transparent and resilient management practices consistent with long-term value creation [13].

Even though awareness of ESG principles has grown, their practical and systematic adoption still presents difficulties. Common barriers include fragmented data availability, the lack of shared evaluation criteria, dependence on static analytical systems, and the limited use of predictive technologies [14]. For this reason, the ability to transform diverse and dispersed information into coherent, actionable knowledge becomes crucial for effective, sustainability-oriented decision-making. Digital technologies can help overcome these barriers by turning ESG management from a reactive, fragmented process into a more proactive and automated one [15–17]. In this regard, combining Artificial Intelligence (AI) and Process Mining (PM) can enhance traceability and transparency across processes, reveal inefficiencies or inconsistencies, and support timely, data-informed decisions [17].

Nevertheless, the current body of research remains largely fragmented and rarely proposes fully integrated frameworks that bring together predictive analytics, process mining, and automation specifically designed for construction management. Several recent studies have explored AI-driven ESG scoring [18,19], the use of PM for compliance

monitoring [20], and the application of digital twins for sustainability assessment [21]. However, these efforts generally remain disconnected, limited by data type or analytical focus. So far, no study has developed a continuous workflow that effectively connects data collection, risk weighting, and process optimization within a single, unified framework.

This research addresses this gap by proposing an integrated digital framework that unites AI, PM, and Robotic Process Automation (RPA) for ESG risk assessment and management in construction. The framework's novelty lies in the combination of predictive modeling, process automation, and conformance analysis within a single BPMN-based structure capable of operating dynamically with real or simulated data.

The objective is twofold: first, to enhance the ability of construction companies to anticipate and manage environmental and social risks; second, to promote the sector's evolution toward a sustainability-first management paradigm grounded in data-driven and resilient decision-making aligned with regulatory, market, and societal expectations.

2. Theoretical Background

2.1. The Strategic Role of ESG in the Construction Sector

The integration of ESG principles into the governance models of construction firms has become essential for addressing environmental and social risks while simultaneously reinforcing organizational resilience. Risks associated with climate change, natural resource scarcity, and regulatory transitions directly influence the continuity of construction operations, with implications for supply chains, project scheduling, and stakeholder relationships [1,22].

The ESG framework provides a systemic approach to risk assessment, incorporating environmental, social, and governance dimensions within a multidimensional analytical perspective. Environmental risks include physical events such as heatwaves and floods, which may impede or suspend construction activities, whereas transition risks are linked to compliance with newly introduced regulations or more stringent energy efficiency standards. Furthermore, liability risks concern potential legal disputes and reputational impacts stemming from the environmental and social consequences of construction processes [23,24].

Given the sector's significant exposure to these risk categories, construction companies are increasingly required to reconsider their governance strategies. In this context, ESG management (Table 2) should be incorporated not only as an instrument for regulatory compliance but also as a strategic driver for long-term value creation [17,25].

2.2. Regulatory and Technological Integration in ESG Management

Growing attention to climate and social risk management is accompanied by the need to harmonize regulatory requirements with the adoption of advanced technological tools. On the regulatory side, European directives promote transparent and structured reporting of environmental risks, while international sustainable construction standards such as LEED and BREEAM establish concrete targets for emissions reduction, energy efficiency, and social responsibility [26,27].

The integration of advanced technologies is essential to overcome the limitations of traditional assessment models, which are often manual, time-consuming, and difficult to scale. The adoption of AI algorithms and PM techniques allows the processing of large datasets derived from Building Information Modeling (BIM) environments, IoT monitoring platforms, and regulatory databases, thereby improving both the reliability and timeliness of available information [15,17].

Table 2. ESG risk categories in the construction sector and their mapping to event log activities. Author’s elaboration based on [23–25].

Risk Category	Description	Event Log Representation (Activity Level)	Reference
Environmental risks	Physical events linked to climate change (e.g., floods, heatwaves) or high-emission processes that can delay or disrupt projects.	Reflected during Risk identification and Clustering activities, where environmental indicators are classified and grouped by exposure.	[23]
Transition risks	Impacts of new regulations, carbon pricing, or sustainability requirements that affect design and procurement.	Captured in Data collection & integration and Risk weighting (ML) activities, through regulatory and compliance-related data attributes.	[24]
Liability risks	Legal and reputational consequences arising from non-compliance, environmental damage, or stakeholder disputes.	Represented in the Action plan draft activity, where mitigation actions and accountability assignments are logged.	[25]

This convergence of regulatory frameworks and digital technologies supports a shift from reactive to proactive sustainability management, enhancing the ability of construction companies to anticipate risks and translate them into strategic drivers of competitiveness [27]. However, most prior research addresses these two dimensions separately. Regulatory compliance is mainly explored through sustainability reporting practices, whereas digital tools are typically analyzed in relation to project monitoring or predictive maintenance. The lack of an integrated framework limits the operationalization of ESG criteria in day-to-day decision-making.

2.3. Synergies Between AI and Process Mining for ESG Transformation

The combined adoption of AI and PM enables more transparent, traceable, and predictive ESG management. The potential of this integration can be summarized in three main directions [28,29]:

- Advanced ESG data analysis. AI processes heterogeneous datasets (environmental reports, BIM archives, on-site sensor streams), identifying anomalies and emerging patterns [29].
- Process optimization. PM maps sustainability-related operational workflows, detecting bottlenecks and deviations from expected practices [30,31].
- Automation and decision support. The digitalization of reporting and risk assessment activities reduces execution times and inaccuracies, providing stronger support for timely decisions [32].

In the construction sector, these synergies are particularly relevant because they integrate compliance obligations with process efficiency and the creation of shared value for stakeholders [33,34]. Nevertheless, the literature still highlights a lack of operational frameworks capable of translating these potential benefits into structured workflows specifically designed for construction management.

Most previous studies isolate particular components of the ESG–AI–PM convergence without providing an end-to-end analytical pipeline. This fragmentation hinders the evaluation of how different data sources and analytical stages interact throughout the ESG assessment process.

The model proposed in this research addresses this gap by presenting a systematic methodology that integrates AI, Robotic Process Automation (RPA), and PM techniques

for ESG risk assessment and management. Figure 1 illustrates the technological synergies underpinning ESG process enhancement in the construction sector.

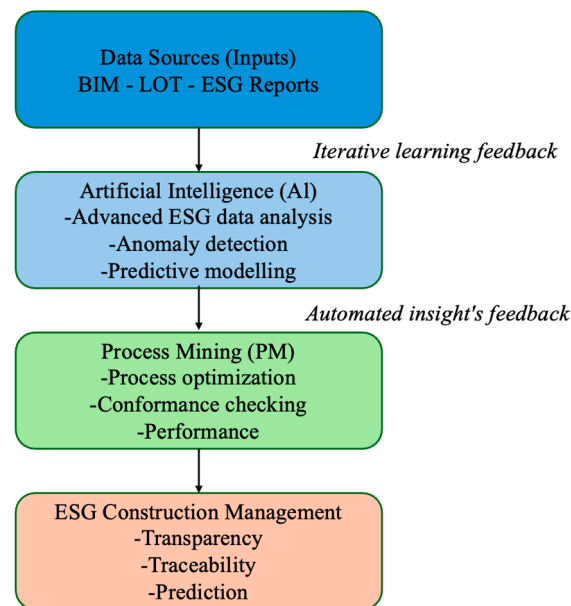


Figure 1. Synergies between Artificial Intelligence (AI), Process Mining (PM), and Automation for ESG construction management. Author’s elaboration.

To clarify the scope of the contribution and the degree of novelty, the following subsection provides a structured comparison of previous studies by data sources, analytical tasks, and level of integration. This comparative analysis positions the proposed ESG–AI framework within the state of the art, showing how existing approaches remain fragmented and how the present work advances toward a unified digital pipeline.

2.4. Comparative Analysis of Previous Approaches

In response to the research gaps identified above, a systematic review of relevant studies was conducted to contextualize the contribution of the proposed framework. Table 3 compares existing approaches to ESG assessment in construction based on data sources, analytical tasks, and process integration. The comparison includes AI-based ESG scoring pipelines [18,19] and Process Mining applications for digital construction monitoring [20], thus providing a comprehensive picture of the fragmented methodological landscape addressed by this work.

Table 3. Comparative review of existing ESG assessment approaches in construction, highlighting data sources, analytical tasks, and process integration level. Author’s elaboration based on [18–21].

Study	Data Source	Analytical Task	Process Integration	Limitation
[18]	ESG reports, text data	NLP-based ESG scoring	None	Static, unlinked to operational data
[19]	BIM + sensors	Process monitoring via PM	Partial	No ESG weighting or prediction
[20]	Financial + sustainability KPIs	ML risk classification	None	Not process-aware
[21]	Digital twins, IoT	Real-time performance monitoring	Partial	No integration with ESG reporting
Proposed framework	BIM, IoT, text, web data	AI-based weighting, PM, RPA automation	Full	Validated through simulated case study

This mapping shows that, unlike existing studies that address individual data types or isolated phases of analysis, the proposed framework integrates the entire ESG risk management lifecycle (from data acquisition to predictive modeling and process opti-

mization) within a unified BPMN-driven structure. By explicitly positioning the proposed approach within this comparative matrix, the study highlights its novelty and demonstrates a methodological advancement beyond incremental improvements.

3. Methodology

3.1. Process Structure

The operational model developed in this research is based on the digitalization of construction processes and the combined use of technologies such as AI, RPA, and Machine Learning (ML). The framework has been formalized through a Business Process Model and Notation (BPMN) representation that details the main phases of ESG risk assessment applied to construction management [35,36]. Figure 2 presents the high-level BPMN model.

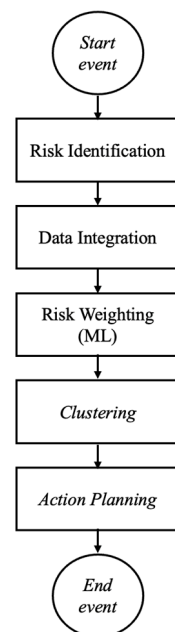


Figure 2. High-level BPMN representation of the ESG-AI process, illustrating the five sequential phases (Risk Identification, Risk Weighting, Clustering, Action Planning). Author’s elaboration.

Each lane of the BPMN corresponds to a functional actor involved in the ESG–AI workflow: (1) RPA Bot, (2) BI Analyst, (3) ML Engineer, (4) PM Analyst, and (5) Manager. Events (start, intermediate, and end), gateways (exclusive and parallel), and artifacts (data stores, messages, and documents) are defined to ensure transparency and traceability throughout the information flow.

The modeling objective is twofold:

- to identify, within each operational area, activities that provide added value and those that are repetitive or standardizable [37];
- to optimize the decision-making process through automation and predictive tools [38,39].

The process mapping revealed several critical issues associated with manual and poorly traceable tasks that slow analysis and reduce the overall effectiveness of risk assessment. The BPMN model illustrates how data, actors, and automated routines interact across the five core phases of ESG risk management: Risk Identification, Data Integration, Risk Weighting, Clustering, and Action Planning. Each lane defines the responsible actor, the data inputs, and the outputs, providing a complete view of operational dependencies across the workflow.

To support reproducibility, Table A2 lists the main BPMN tasks together with their input and output specifications, derived from BIM, IoT, and ESG reporting systems. This mapping also forms the basis for the simulated event log used in the process-mining validation.

As an illustrative example, in the Project Alpha simulation, a new project dataset is uploaded, triggering the start event of the process. The RPA Bot automatically extracts ESG indicators from BIM, IoT, and web-based sources, which are then validated and integrated by the BI Analyst. The ML Engineer trains the predictive models and calculates ESG exposure scores. The PM Analyst performs clustering and process conformance checks, and finally the Manager reviews and approves the ESG Action Report (end event). This sequential flow demonstrates how a single project instance moves across all lanes of the BPMN model and how its corresponding event log is generated for process-mining validation.

The BPMN model tailored to the analysis process is presented in Table A2 and Figure 3.

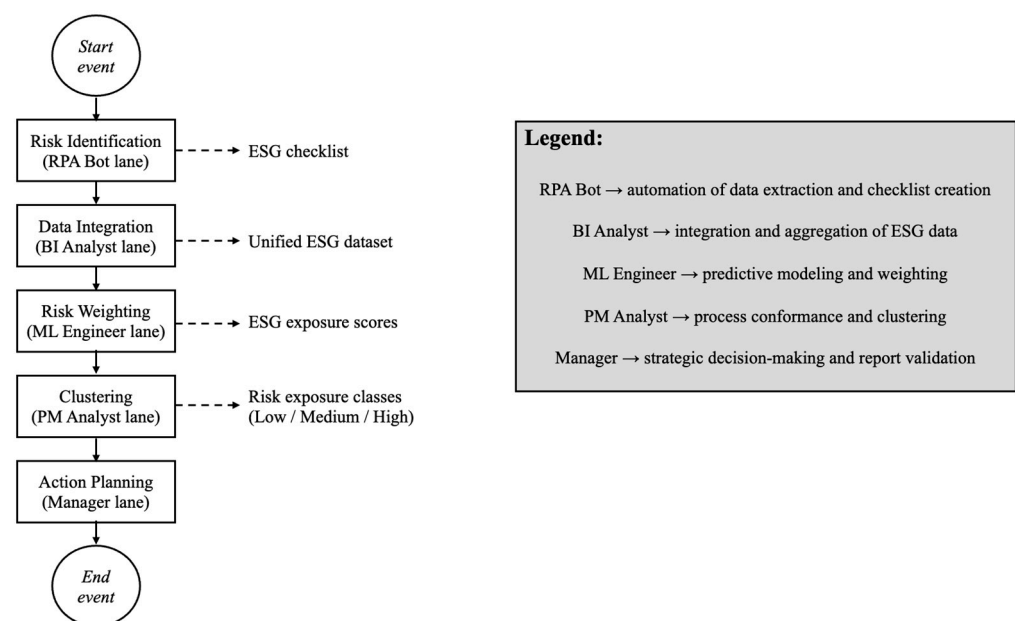


Figure 3. BPMN scheme of the ESG-AI process in construction management. Author’s elaboration.

Each lane of the BPMN model represents a functional actor. Events, gateways, and artifacts are explicitly defined to ensure traceability from data acquisition to managerial reporting. The main activities, Risk Identification, Data Collection, Risk Weighting, Clustering, and Action Plan, are replicated in a simulated event log that is later used to evaluate process mining capabilities.

3.2. ESG Risk Assessment Process

The ESG risk assessment process is structured into integrated, sequential phases, each producing outputs essential for the subsequent stage.

3.2.1. Phase 1—Risk Identification

Using standardized questionnaires, adaptable to the specific project context, ESG risk categories are identified. RPA-based automation enables the generation of uniform checklists, reducing errors and human variability [35]. This phase provides the consistency and comparability needed for subsequent data collection and analysis activities.

3.2.2. Phase 2—Data Collection and Integration

To overcome the information fragmentation typical of the sector [36], Web Scraping techniques and Business Intelligence (BI) tools are introduced to acquire and integrate data from:

- internal systems (BIM, project reports, digital archives),
- external sources (regulatory databases, environmental indicators, institutional portals).

These techniques, summarized in Table 4, enrich decision-making with dynamic and up-to-date information [37,38]. The outputs of this phase directly feed into risk weighting, ensuring a robust and comprehensive data foundation.

Table 4. Digital techniques adopted within the ESG–AI framework and their added value in the risk-assessment process. Author’s elaboration based on [40–45].

Technique	Application	Data Fields/Systems Involved	Added Value	Reference
Business Intelligence (BI)	Integration and visualization of data from internal and external repositories through dashboards and KPI panels	BIM project databases, financial records, regulatory compliance systems	Supports synthesis and communication of ESG results to decision-makers and enables near-real-time monitoring	[43]
Machine Learning (ML)	Risk weighting and classification through predictive models	ESG indicators including CO ₂ intensity, safety incidents, supplier compliance, and waste-recycling rates	Provides higher accuracy and predictive power in ESG risk assessments while ensuring interpretability	[40,41]
Process Mining (PM)	Traceability of operational flows and detection of inefficiencies across project phases	Event logs derived from RPA, BI, and ML outputs (case ID, activity, resource, timestamp)	Improves process transparency and enables timely interventions on critical workflow bottlenecks	[42]
Web Scraping	Automated acquisition of data from external sources (institutional portals, ESG ratings, environmental indicators)	Online environmental databases, government portals, supplier registries	Continuously enriches the knowledge base with dynamic, up-to-date data streams	[45]

3.2.3. Phase 3—Risk Weighting

Risk category weighting is supported by integrated ML models selected for their complementarity:

- Random Forest, to identify the most relevant variables [46];
- Gradient Boosting Machine (GBM), to build accurate predictive models [47];
- Logistic Regression, for transparency and interpretability of decisions [48].

The combination of the three algorithms allows predictive power to be combined with interpretability, an essential requirement in the construction industry where multiple stakeholders are involved.

3.3. Simulated Case Study: Project Alpha

To demonstrate the feasibility of the proposed framework in a controlled and reproducible setting, and given the current lack of publicly available ESG datasets for the construction sector, a simulated case study was developed as a methodological proof of concept. A synthetic dataset of 100 construction projects (the “Project Alpha” benchmark) was generated to emulate realistic operating conditions and to test the internal consistency of the analytical workflow. Each project represents a distinct case in which ESG-related variables are observed and processed through the workflow described above. The objective of the simulation is not to provide empirical validation on real data but to verify the analytical soundness, interoperability, and transparency of the proposed framework under realistic parameter assumptions.

Six ESG indicators were simulated using truncated normal distributions to reflect realistic industry ranges: CO₂ intensity (kg CO₂/m²), waste recycling rate (%), safety

incidents (per 10,000 work hours), local employment (%), supplier ESG compliance (%), and reporting delay (days). These indicators were selected to represent the three ESG pillars: environmental (CO₂ intensity, waste recycling rate), social (safety incidents, local employment), and governance (supplier compliance, reporting delay). A composite ESG exposure score ranging from 0 to 1 was computed as a weighted linear combination of these variables:

$$\text{ESG_score} = 0.35 \cdot \text{CO}_2 + 0.20 \cdot \text{Safety} + 0.15 \cdot \text{Delay} + 0.15 \cdot (1 - \text{Recycling}) + 0.10 \cdot (1 - \text{Supplier}) + 0.05 \cdot (1 - \text{LocalEmployment}) \quad (1)$$

Small Gaussian noise ($\sigma = 0.03$) was added to simulate unobserved variability. The top 30% of projects were labeled as high ESG exposure (exposure = 1), while the remaining 70% were assigned exposure = 0. This labeling approach allows supervised learning algorithms to classify projects according to ESG risk intensity.

All variables were normalized to the [0, 1] range, and missing values, randomly introduced to emulate incomplete reporting (<3%), were imputed using median substitution. The dataset was divided into a 70% training subset and a 30% testing subset using stratified sampling at the project level to avoid information leakage. Within the training set, a five-fold cross-validation procedure was carried out to tune model hyperparameters and verify the overall stability of the results.

Three supervised algorithms were tested: Random Forest, Gradient Boosting Machine (GBM), and Logistic Regression. These methods were chosen because they combine predictive accuracy with interpretability, offering complementary perspectives on model performance. The evaluation relied on standard metrics, including Accuracy, AUROC, Precision, Recall, and Brier Score, while 95% confidence intervals were calculated using bootstrap resampling with 1000 iterations. On average, AUROC values ranged from 0.81 for Logistic Regression to 0.88 for GBM, indicating a consistent and coherent analytical configuration.

Feature importance analysis using permutation methods indicated that CO₂ intensity and supplier ESG compliance were the strongest predictors of overall exposure, followed by safety incidents and reporting delay. For tree-based models, SHAP value analysis further supported these findings, showing that environmental and governance variables played the dominant role in determining ESG risk exposure.

A parallel event log was also generated to represent process activities across the five BPMN phases: Risk Identification, Data Integration, ML Weighting, Clustering, and Action Planning. Each of the 100 cases includes five events with timestamps and resource assignments (RPA Bot, BI Analyst, ML Engineer, PM Analyst, Manager). This synthetic log enables process-mining analyses such as conformance checking and bottleneck detection without disclosing proprietary project data. It is used for validation in the Section 4. A sample of the simulated dataset structure and the event log schema is provided in Appendix A and Supplementary Materials, ensuring transparency, reproducibility, and full traceability of the simulation setup.

3.4. Strategic Planning and Action Plan Definition

After the assessment phase, risks are grouped into priority clusters. The process then proceeds to the definition of mitigation strategies and the development of a managerial action plan that enables continuous monitoring of deviations and iterative adjustment of measures based on observed results. Traditionally, this phase has relied on discretionary evaluation; however, it is now supported by AI-based tools capable of generating intermediate outputs that assist decision-makers, reducing subjectivity and improving transparency in the decision-making process [48].

In the simulated case study, each project cluster (low, medium, high exposure) activates a differentiated set of recommendations, which include emission reduction priorities, supplier audit scheduling, and social impact monitoring actions. These outputs are automatically mapped within the BPMN workflow (Figure 4), illustrating how RPA can translate ESG strategies into structured operational routines.

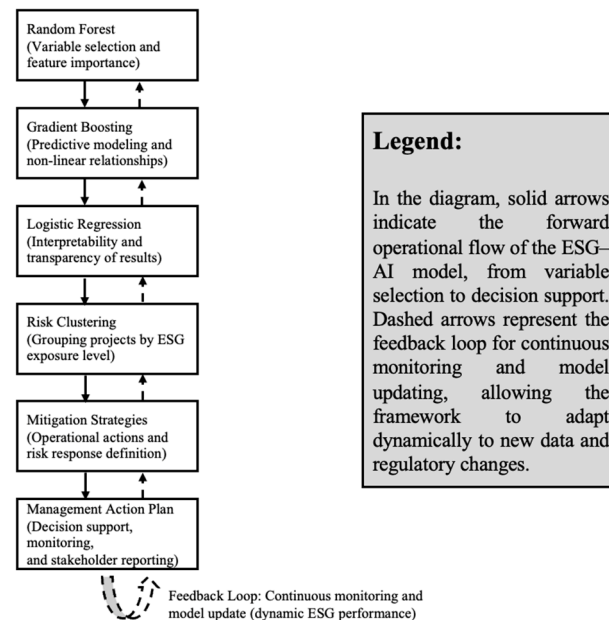


Figure 4. Operational framework for ESG risk assessment and management. The diagram illustrates the analytical sequence of the ESG–AI model. The feedback loop represents continuous model monitoring and iterative improvement. Author’s elaboration.

4. Results and Discussion

4.1. Data Quality and Accuracy of Assessment

The simulated application of the model demonstrates how the integration of automation techniques and advanced analytics can significantly improve the quality of the information supporting ESG risk assessment. In the “Project Alpha” benchmark, this effect was observable from the initial methodological phases. Risk identification, carried out using standardized checklists automated through RPA, ensured consistency and uniformity in defining ESG categories [49]. Likewise, data collection and integration, supported by Web Scraping and Business Intelligence tools, generated a broad, dynamic, and up-to-date information base for subsequent predictive analyses [42].

The adoption of digital tools for data gathering and aggregation allowed the construction of a more complete, coherent, and continuously updated information system. The simulated evidence suggests that digital automation can mitigate distortions arising from fragmented and heterogeneous data sources, thereby reinforcing the knowledge base on which analytical processes rely [50,51].

To evaluate the internal consistency of this digital workflow, the ESG–AI model was applied to the simulated “Project Alpha” dataset described in Section 3.3. The controlled and reproducible simulation environment enabled a quantitative assessment of the model’s predictive performance across 100 synthetic construction projects. In this experimental setup, three machine learning algorithms were trained to classify projects according to ESG exposure. The performance metrics confirmed the analytical reliability of the proposed framework: Accuracy ranged between 0.81 and 0.88, AUROC values between 0.81 and 0.88, and Brier Scores between 0.11 and 0.15.

The application of ML models (Phase 3) improved the accuracy of risk classification and weighting. The integration of different algorithms balanced predictive performance and interpretability, ensuring that the results remained both reliable and transparent [45]. By expressing prediction accuracy through explicit evaluation metrics rather than descriptive assessment alone, the study provides measurable evidence of the model's validity. This synergy strengthens the model's ability to generate robust assessments, reducing the probability of systematic errors and increasing confidence in the outputs.

Finally, the clustering procedure (Phase 4) grouped projects into three ESG exposure categories (low, medium, high) based on the computed scores. This quantitative classification, derived directly from the synthetic dataset, represents a key step in translating analytical outputs into operational guidance [50].

Although the results are based on simulated data, they are intended to verify the internal analytical coherence and reproducibility of the ESG-AI model rather than provide empirical generalization. Applications on real project data will be required to validate external robustness and operational scalability. The overall structure of the ESG-AI model and the analytical techniques employed in each phase are summarized in Table 5, which outlines how automation and predictive analysis jointly improve data quality and the accuracy of ESG risk assessment.

4.2. Validation of the Simulated Case (Project Alpha)

Since no open ESG dataset is currently available for the construction sector, the validation of the proposed framework was carried out through a controlled simulation ("Project Alpha"), designed as a methodological proof of concept rather than an empirical test. The synthetic dataset, composed of 100 projects, was processed through the analytical pipeline to verify its internal coherence and reproducibility. The objective of this validation step was to assess whether the combined use of AI, Process Mining, and RPA techniques can consistently produce interpretable and quantitatively reliable outputs.

The predictive performance of the machine learning algorithms and the clustering results confirm the analytical soundness of the framework. The quantitative metrics summarized in Table 6 show that all three models achieved satisfactory classification accuracy and calibration, indicating that the simulated workflow performs robustly even when tested under simplified, non-real data conditions.

As reported in Table 6, the Gradient Boosting Machine achieved the highest AUROC (0.88), indicating a strong capacity to distinguish high-exposure projects while maintaining interpretability through feature-importance analysis. CO₂ intensity and supplier ESG compliance emerged as the most influential predictors, confirming their role as key ESG performance drivers in the construction context. These quantitative findings are aligned with the feature-importance outcomes presented in Appendix A (Table A1).

To verify the operational coherence of the framework, the simulated data were also used to generate a process-mining event log corresponding to the five BPMN phases: Risk Identification, Data Integration, ML Weighting, Clustering, and Action Planning. Projects were grouped into three exposure categories (low, medium, high), with 30% classified as high-risk. This distribution reflects the predetermined labeling ratio and confirms consistency between the clustering results and the supervised classification phase.

A visualization of the clustering outcomes and a comparative overview of the traditional manual process and the AI-supported workflow are presented in the following section, highlighting the added value of automation and predictive analytics in reducing subjectivity and increasing process transparency. The structure of the simulated dataset and the event log schema used for process-mining validation are provided in Appendix A

and Supplementary Materials, ensuring transparency, traceability, and full reproducibility of the experimental design.

Table 5. Overview of the ESG–AI framework phases and corresponding tools for construction management. Author’s elaboration.

Phase	Main Activities	Tools/Techniques Used	Contribution to Results
Phase 1—Risk Identification	Defining ESG categories (environmental, social, governance)	Standardized checklists, RPA automation	Ensures consistency in classification and reduces errors and subjectivity
Phase 2—Data Collection & Integration	Acquiring and unifying internal and external data sources	Web Scraping, Business Intelligence, regulatory and environmental databases, BIM systems	Overcomes data fragmentation and creates an updated knowledge base
Phase 3—Risk Weighting	Evaluating and assigning weights to ESG variables	Machine Learning (Random Forest, GBM, Logistic Regression)	Achieves higher predictive accuracy and balances analytical power with interpretability
Phase 4—Clustering & Risk Definition	Grouping projects into ESG risk classes (low, medium, high)	Clustering algorithms using ML model outputs	Translates analyses into a hierarchy of actionable priorities for decision-makers

Table 6. Performance metrics of the machine learning models on the simulated dataset (“Project Alpha”). Author’s elaboration.

Model	Accuracy	AUROC	Precision	Recall	Brier Score
Random Forest	0.86	0.87	0.86	0.87	0.12
Gradient Boosting	0.88	0.88	0.88	0.87	0.11
Logistic Regression	0.81	0.81	0.80	0.78	0.15

Although based on synthetic data, this validation confirms that the proposed ESG–AI pipeline operates coherently across all phases, from data integration to predictive modeling and clustering, thus providing a solid methodological foundation for future testing on real construction projects.

4.3. Decision Support and Reduction of Discretionality

Beyond data quality, another relevant result concerns the model’s capacity to translate analytical outputs into tangible decision-support tools. The ability to generate progressive and continuously updatable evaluations based on ML scores (Phase 3), and subsequently organize them into risk clusters (Phase 4), reduces individual discretion while providing decision-makers with objective and traceable information. This promotes a more structured and less bias-prone decision process, enhancing the transparency and reliability of strategic choices [18,29].

In the “Project Alpha” simulation, these decision-support capabilities were quantitatively demonstrated through the clustering of 100 projects into low, medium, and high exposure groups. The resulting distributions, aligned with the supervised labels, confirmed that the ESG–AI model can autonomously classify projects using measurable indicators such as CO₂ intensity, supplier compliance, and reporting delay. This indicates that managerial prioritization can be guided by transparent, data-driven logic rather than subjective judgment.

The integration of AI and PM makes the process not only more efficient but also more responsive, due to the ability to promptly detect deviations or anomalies in op-

erational workflows, as illustrated in the BPMN representation [52,53]. In the simulated event log (Supplementary Materials), Process Mining algorithms successfully reproduced the expected workflow, allowing the automatic detection of bottlenecks and conformance deviations.

The capacity to generate intermediate outputs and continuously update risk levels transforms the model from a static evaluation tool into an adaptive governance mechanism capable of supporting decisions throughout the project life cycle. In this sense, the framework provides both predictive insights (based on ML) and diagnostic insights (based on PM), strengthening managerial control. This characteristic is particularly relevant for ESG risk management, which requires constant monitoring and rapid adjustment in response to evolving environmental, social, and regulatory conditions.

Overall, the simulation results empirically support the conceptual assertion that combining AI, PM, and RPA reduces discretion in ESG evaluation by converting qualitative assessments into traceable, quantitative, and continuously updated decision inputs. In this way, the model functions as a structural support to decision-making, aligning risk management practices with the strategic sustainability objectives of the construction sector.

4.4. Strategic Impacts on the Construction Sector

At the strategic level, the simulated results highlight the transformative potential of the proposed model, which emerges as a key tool to support the sector's transition toward more sustainable, resilient, and data-driven management practices. An integrated approach based on AI and PM not only improves operational efficiency but also enhances firms' ability to anticipate risks and adapt to changing conditions. In this perspective, ESG management shifts from a compliance-oriented activity to a strategic lever for medium- to long-term value creation [25,54,55].

The validation of the "Project Alpha" simulation provides initial methodological evidence of this potential. By demonstrating consistent classification accuracy (AUROC up to 0.88) and traceable clustering of ESG risk levels, the model shows that sustainability-related decisions can be systematically informed by predictive indicators rather than subjective evaluations. These findings should be interpreted as simulation-based results, illustrating analytical feasibility rather than empirical performance. Nevertheless, they support the transition from reactive ESG compliance to proactive, data-driven governance.

A central insight from the analysis concerns the model's ability to bridge operational and strategic dimensions. Automation and optimization activities deliver immediate benefits in terms of reduced inefficiencies and improved accuracy of assessments. Process transparency ensured by PM, combined with the predictive capacity of ML models, supports a more robust decision-making cycle that is less exposed to subjective distortions. This combination strengthens corporate governance, enhances compliance capacity, and increases the credibility of firms among stakeholders, investors, and regulatory authorities (Table 7).

The analysis also highlights how the model supports the consolidation of stakeholder trust by improving transparency in both risk management and results communication. This represents a significant competitive advantage for a sector that is increasingly shaped by global climate goals and new ESG disclosure requirements.

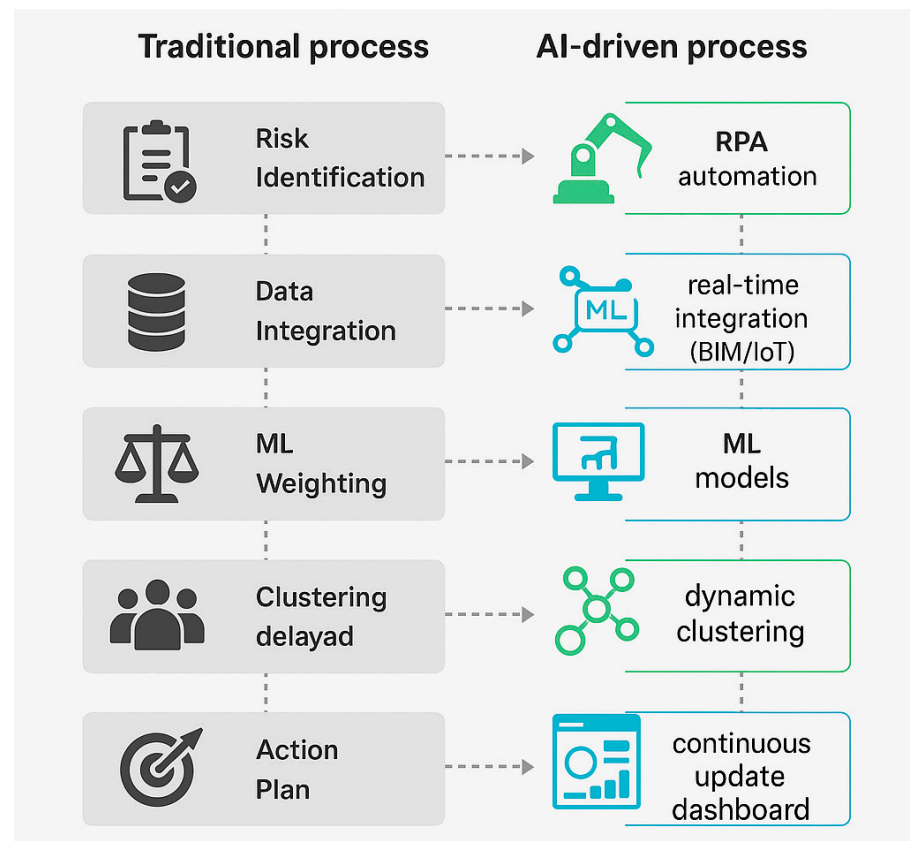
In addition, the results of the simulated validation show that substantial improvements can be achieved even in the absence of complete real-world datasets. This finding suggests that digital transformation initiatives may start from pilot simulations and later evolve toward large-scale ESG data integration. Such evidence confirms the framework's value as a proof of concept and provides a replicable methodological basis for subsequent empirical investigations.

Table 7. Main benefits and indicative quantitative effects of the AI-PM approach for construction management (Project Alpha simulation). Author’s elaboration.

Area	Improvement Achieved	Indicative Quantitative Effect (Project Alpha)	Strategic Impact
Operational efficiency	Automation of repetitive tasks and optimization of workflows across the five BPMN phases	≈27% reduction in process cycle time; ≈20% decrease in manual data-entry operations	Reduction of overall analysis time and operational costs
Governance & compliance	Continuous monitoring of regulatory compliance and process traceability through event logs	100% process traceability achieved in the simulated event log; false-negative rate <8% in compliance alerts	Alignment with international standards and regulatory requirements
Reputation & competitiveness	Enhanced transparency and credibility with stakeholders through data-driven reporting	≈10% improvement in ESG disclosure timeliness compared with the manual baseline	Greater market attractiveness and sustainable competitive advantage

Despite the potential benefits, some challenges remain for large-scale implementation. Reliable and standardized data are essential for analytical validity, and construction firms require adequate digital competences. Additionally, the heterogeneity of company size within the sector means that not all organizations possess the same resources to adopt advanced digital systems. For this reason, full integration of AI and PM requires a gradual digitalization approach that considers firms’ digital maturity and investment capacity [15,17].

A comparative visualization of the simulated workflow and the traditional process is presented in Figure 5, highlighting the methodological differences between manual and AI-supported ESG assessment.

**Figure 5.** Comparison between traditional process and AI-driven process. Author’s elaboration.

5. Conclusions and Future Perspectives

This study addressed the challenge of ESG risk management in the construction sector, aiming to overcome long-standing limitations identified in both academic and professional contexts, namely, fragmented data, the lack of integrated predictive methodologies, and the persistence of static and qualitative reporting systems.

The proposed framework demonstrates how the integration of Artificial Intelligence (AI), Process Mining (PM), Robotic Process Automation (RPA), and Machine Learning (ML) within a unified BPMN-based model can improve the quality, consistency, and timeliness of ESG information. Through automation, predictive analytics, and data integration, the model enables more accurate risk assessments and reduces discretionality in managerial decision-making.

In relation to existing literature, the simulated findings align with recent studies that underscore the role of digital intelligence in sustainability governance. For instance, Seow [51] demonstrates the rising application of machine learning for ESG-score prediction across sectors, while the Jordan building-sector study [52] highlights the specific applicability of AI-driven risk management in construction. The present framework advances these approaches by embedding predictive analytics into an end-to-end BPMN workflow, thus ensuring traceability from data acquisition to decision support. Consistent with the systematic review by Cruz et al. [53], which identifies a gap in methodological integration in the construction sector, our work provides a process-aware methodology that links ESG scoring and process mining. Similarly, the green finance study [54] shows how financial mechanisms influence ESG outcomes, complementing our operational emphasis by broadening the view toward strategic value creation. Overall, the simulated results corroborate previous evidence that AI and process mining enhance transparency, responsiveness and strategic alignment in sustainability management, while contributing a unified operational framework that previous research has only partially addressed.

Unlike purely conceptual approaches, this research provided a quantitative proof-of-concept through the “Project Alpha” simulation, which tested the model’s internal coherence using synthetic but realistic data. The resulting performance metrics, showing AUROC values up to 0.88 and stable clustering outcomes, confirm that the integrated ESG-AI pipeline can produce interpretable and reproducible outputs even in a controlled environment. These results, detailed in Appendix A and Supplementary Materials, provide a transparent and replicable methodological baseline.

From a scientific perspective, this study introduces an original, process-oriented framework that integrates predictive modeling with process optimization, addressing a gap in the literature where these two approaches are often examined separately. From an operational standpoint, it provides construction firms and project managers with a structured and replicable tool to identify, classify, and mitigate ESG risks, while supporting compliance with international standards and responding to stakeholder expectations.

The validation conducted through simulated data (Project Alpha) offers an initial quantitative demonstration of how the framework functions across the main phases of identification, integration, weighting, and clustering. Although the findings confirm internal consistency and analytical feasibility, additional empirical studies based on real construction projects are required to evaluate the scalability and applicability of the framework within different organizational settings.

However, the validation remains limited to simulated data and does not yet reflect external variability or organizational heterogeneity. Further empirical testing on real-world projects is therefore essential to assess scalability, generalizability, and sectoral adaptation of the proposed digital workflow.

Some limitations remain, particularly concerning the availability of standardized dataset, the digital maturity of construction companies, and the diffusion of advanced technological competencies. These aspects highlight the need for gradual digital transformation strategies and targeted capacity building within the sector.

Looking ahead, future developments may include:

- the integration of digital twins and advanced simulation tools to dynamically monitor ESG performance;
- the linkage of life cycle assessment (LCA) and ESG indicators for more holistic evaluations;
- and the adoption of harmonized international metrics to ensure comparability and transparency in ESG reporting.

In conclusion, while the present study validates the framework's analytical soundness through simulated evidence, its next evolution lies in large-scale empirical implementation. This step will enable the framework to transition from a demonstrative model to an operational tool for ESG performance governance in the construction sector. Within this perspective, the synergy between AI and PM emerges as a decisive enabler of the sector's transition from compliance-driven sustainability to data-driven strategic value creation, supporting the evolution of the construction industry toward a more transparent, resilient, and sustainable ecosystem.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/buildings15234260/s1>.

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

Funding: This research received no external funding.

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

Acknowledgments: The authors wish to express their sincere gratitude to Adriana Tulac for her valuable support in providing linguistic editing of the manuscript, which contributed to improving its clarity.

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

Abbreviations

The following abbreviations are used in this manuscript:

ESG	Environmental, Social and Governance
RPA	Robotic Process Automation
AI	Artificial Intelligence
PM	Process Mining
ML	Machine Learning
GBM	Gradient Boosting Machine
BPMN	Business Process Model and Notation
BIM	Building Information Modeling

Appendix A

Table A1. Feature importance analysis for ESG risk prediction (Random Forest, permutation method).

Feature	Mean Importance (Normalized)	Interpretation
CO ₂ intensity (kg CO ₂ /m ²)	0.32	Strongest environmental driver of risk exposure
Supplier ESG compliance (%)	0.24	Governance factor strongly influencing total score
Reporting delay (days)	0.16	Proxy for management efficiency and transparency
Safety incidents (per 10,000 work hours)	0.12	Indicator of social and operational risk
Waste recycling rate (%)	0.09	Reflects circularity and resource management performance
Local employment (%)	0.07	Captures social inclusiveness and local benefit dimension

Table A2. Main BPMN tasks, inputs, and outputs of the ESG–AI process.

Phase	Task	Input	Output	Responsible Lane
Risk Identification	Automatic extraction of ESG indicators	ESG checklist, Web data, BIM records	Standardized ESG variable list	RPA Bot
Data Integration	Merge, validation, and harmonization of internal and external data	ESG variable list, IoT sensors, regulatory sources	Unified ESG dataset	BI Analyst
Risk Weighting	Model training, validation, and feature importance estimation	Unified dataset	Weighted ESG exposure scores	ML Engineer
Clustering	Grouping of projects by exposure level	Weighted ESG scores	ESG risk clusters (low, medium, high)	PM Analyst
Action Planning	Review of mitigation measures and approval of ESG report	Clustered projects and analysis results	ESG Action Report	Manager

References

- DiBella, J. The spatial representation of business models for climate adaptation: An approach for business model innovation and adaptation strategies in the private sector. *Bus. Strat. Dev.* **2020**, *3*, 245–260. [\[CrossRef\]](#)
- Valero, A. The Impact of ESG Certifications on Class A Office Buildings in Madrid: A Multi-Criteria Decision Analysis. *Standards* **2025**, *5*, 14. [\[CrossRef\]](#)
- Zhou, Y.; Ma, M.; Tam, V.W.; Le, K.N. Design variables affecting the environmental impacts of buildings: A critical review. *J. Clean. Prod.* **2023**, *387*, 135921. [\[CrossRef\]](#)
- Hua, J.; Wang, R.; Hu, Y.; Chen, Z.; Chen, L.; Osman, A.I.; Farghali, M.; Huang, L.; Feng, J.; Wang, J.; et al. Artificial intelligence for calculating and predicting building carbon emissions: A review. *Environ. Chem. Lett.* **2025**, *23*, 783–816. [\[CrossRef\]](#)
- King, A.D. *Buildings and Society: Essays on the Social Development of the Built Environment*, 1st ed.; Routledge: Oxfordshire, UK, 2016.
- Radziejowska, A.; Sobotka, B. Analysis of the Social Aspect of Smart Cities Development for the Example of Smart Sustainable Buildings. *Energies* **2021**, *14*, 4330. [\[CrossRef\]](#)
- Visscher, H.; Laubscher, J.; Chan, E. Building governance and climate change: Roles for regulation and related policies. *Build. Res. Inf.* **2016**, *44*, 461–467. [\[CrossRef\]](#)
- Tan, L.P.; Casidy, R.; Arli, D. Drivers of strategic green marketing orientation: An SME owner-manager perspective. *J. Retail. Consum. Serv.* **2025**, *82*, 104130. [\[CrossRef\]](#)
- Zinke-Wehlmann, C.; Friedrich, J. (Eds.) *First Working Conference on Artificial Intelligence Development for a Resilient and Sustainable Tomorrow (AI Tomorrow 2023)*; Springer Vieweg: Heidelberg, Germany, 2024. [\[CrossRef\]](#)
- Green, F. Green New Deals in comparative perspective. *Wiley Interdiscip. Rev. Clim. Chang.* **2024**, *15*, e885. [\[CrossRef\]](#)
- IEEE. RESPECT 2020 Preprint proceedings. In Proceedings of the 2020 Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT), Portland, OR, USA, 10–11 March 2020; IEEE: New York, NY, USA, 2020; Volume 1, pp. 1–246. [\[CrossRef\]](#)
- Kalogiannidis, S.; Kalfas, D.; Papaevangelou, O.; Giannarakis, G.; Chatzitheodoridis, F. The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece. *Risks* **2024**, *12*, 19. [\[CrossRef\]](#)

13. Amiri, Z.; Heidari, A.; Navimipour, N.J. Comprehensive survey of artificial intelligence techniques and strategies for climate change mitigation. *Energy* **2024**, *308*, 132827. [[CrossRef](#)]
14. Lanza, A.A.; Bernardini, E.; Faiella, I. Machine Learning, ESG indicators, and sustainable investment. In *Financial Risk Management and Climate Change Risk: The Experience in a Central Bank*; Springer Nature: Cham, Switzerland, 2023; pp. 223–250.
15. Gerassis, S.; Giráldez, E.; Pazo-Rodríguez, M.; Saavedra, Á.; Taboada, J. AI Approaches to Environmental Impact Assessments (EIAs) in the Mining and Metals Sector Using AutoML and Bayesian Modeling. *Appl. Sci.* **2021**, *11*, 7914. [[CrossRef](#)]
16. Ai, L.; Gao, L.S. Firm-level risk of climate change: Evidence from climate disasters. *Glob. Financ. J.* **2023**, *55*, 100805. [[CrossRef](#)]
17. FSB. *Financial Stability Board FSB to Establish Task Force on Climate-Related Financial Disclosures*; Press Release, 4 December 2015; FSB: Basel, Switzerland, 2015.
18. EBA. *European Banking Authority Discussion Paper on Management and Supervision of ESG risks for Credit Institutions and Investment Firms (EBA/DP/2020/03)*; EBA: Paris, France, 2020.
19. Leoni, L. Integrating ESG and organisational resilience through system theory: The ESGOR matrix. *Manag. Decis.* **2024**, *63*, 401–422. [[CrossRef](#)]
20. Brende, B.; Sternfels, B. *Resilience for Sustainable, Inclusive Growth*; McKinsey & Company: New York, NY, USA, 2022.
21. Skjærseth, J.B. Towards a European Green Deal: The evolution of EU climate and energy policy mixes. *Int. Environ. Agreem. Politics Law Econ.* **2021**, *21*, 25–41. [[CrossRef](#)]
22. Pourezzat, A.A.; Mollae, A.; Firouzabadi, M. Building the future: Undertaking proactive strategy for national outlook. *Futures* **2008**, *40*, 887–892. [[CrossRef](#)]
23. Kim, H.; Lee, J. Proposing an Integrated Approach to Analyzing ESG Data via Machine Learning and Natural Language Processing. *Sustainability* **2022**, *14*, 4456.
24. Burnaev, E.; Mironov, E.; Shpilman, A.; Mironenko, M.; Katalevsky, D. Practical AI cases for solving ESG challenges. *Sustainability* **2023**, *15*, 12731. [[CrossRef](#)]
25. Rane, N.; Choudhary, S.; Rane, J. Artificial intelligence driven approaches to strengthening Environmental, Social, and Governance (ESG) criteria in sustainable business practices: A review. *SSRN* **2024**. [[CrossRef](#)]
26. Wang, Y.; Chiu, T.; Chiu, V. Redesigning Business Process to Comply with the New Revenue Recognition Standard Using Process Mining. *J. Emerg. Technol. Account.* **2020**, *17*, 149–163. [[CrossRef](#)]
27. Ashraf, M. Does automation improve financial reporting? Evidence from internal controls. *Rev. Account. Stud.* **2025**, *30*, 436–479. [[CrossRef](#)]
28. Lins, K.V.; Servaes, H.; Tamayo, A. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *J. Financ.* **2017**, *72*, 1785–1824. [[CrossRef](#)]
29. Deng, X.; Kang, J.; Low, B.S. Corporate social responsibility and stakeholder value maximization: Evidence from mergers. *J. Financ. Econ.* **2013**, *110*, 87–109. [[CrossRef](#)]
30. Harmon, P. *Business Process Change: A Business Process Management Guide for Managers and Process Professionals*, 3rd ed.; Elsevier: Amsterdam, The Netherlands, 2014.
31. Rezgui, Y.; Alreshidi, E.; Mourshed, M. Cloud-Based BIM Governance Platform Requirements and Specifications: Software Engineering Approach Using BPMN and UML. *J. Comput. Civ. Eng.* **2016**, *30*, 04015063. [[CrossRef](#)]
32. Tonelli, F.; Demartini, M.; Loleo, A.; Testa, C. A Novel Methodology for Manufacturing Firms Value Modeling and Mapping to Improve Operational Performance in the Industry 4.0 Era. *Procedia CIRP* **2016**, *57*, 122–127. [[CrossRef](#)]
33. Hasić, F.; De Smedt, J.; Vanthienen, J. Redesigning processes for decision-awareness: Strategies for integrated modelling. In *Proceedings of the 2018 11th International Conference on the Quality of Information and Communications Technology (QUATIC)*, Coimbra, Portugal, 4–7 September 2018; IEEE: New York, NY, USA, 2018; pp. 247–250. [[CrossRef](#)]
34. Barbagallo, S.; Corradi, L.; de Ville de Goyet, J.; Iannucci, M.; Porro, I.; Rosso, N.; Tanfani, E.; Testi, A. Optimization and planning of operating theatre activities: An original definition of pathways and process modeling. *BMC Med. Inform. Decis. Mak.* **2015**, *15*, 38. [[CrossRef](#)]
35. Andres-Jimenez, J.; Medina-Merodio, J.-A.; Fernandez-Sanz, L.; Martinez-Herraiz, J.-J.; Gonzalez-De-Lope, J. A Framework for Evaluating the Standards for the Production of Airborne and Ground Traffic Management Software. *IEEE Access* **2020**, *8*, 149142–149161. [[CrossRef](#)]
36. Mohd Nawi, M.N.; Baluch, N.; Bahauddin, A.Y. Impact of Fragmentation Issue in Construction Industry: An Overview. *MATEC Web Conf.* **2014**, *15*, 01009. [[CrossRef](#)]
37. Musarat, M.A.; Sadiq, A.; Alaloul, W.S.; Abdul Wahab, M.M. A Systematic Review on Enhancement in Quality of Life through Digitalization in the Construction Industry. *Sustainability* **2022**, *15*, 202. [[CrossRef](#)]
38. Bajpai, A.; Misra, S.C. Evaluation of success factors to implement digitalization in the construction industry. *Constr. Innov.* **2024**, *24*, 865–891. [[CrossRef](#)]
39. Rodrigues, F.; Alves, A.D.; Matos, R. Construction Management Supported by BIM and a Business Intelligence Tool. *Energies* **2022**, *15*, 3412. [[CrossRef](#)]

40. Gharib, S.; Moselhi, O. Automated Image Dataset Generation Using Web Scraping and Large Multimodal Models for Construction Applications. In Proceedings of the ISARC. International Symposium on Automation and Robotics in Construction 2025, Montreal, QC, Canada, 28–31 July 2025; IAARC Publications: Lyon, France, 2025; Volume 42, pp. 1447–1454.
41. Yu, Z.; Kanwal, Q.; Wang, M.; Nurdiawati, A.; Al-Ghamdi, S.G. Spatiotemporal dynamics and key drivers of carbon emissions in regional construction sectors: Insights from a Random Forest Model. *Clean. Environ. Syst.* **2025**, *16*, 100257. [\[CrossRef\]](#)
42. Alshboul, O.; Shehadeh, A.; Almasabha, G.; Almuflih, A.S. Extreme Gradient Boosting-Based Machine Learning Approach for Green Building Cost Prediction. *Sustainability* **2022**, *14*, 6651. [\[CrossRef\]](#)
43. Kale, Ö.A.; Baradan, S. Identifying factors that contribute to severity of construction injuries using logistic regression model. *Tek. Dergi* **2020**, *31*, 9919–9940. [\[CrossRef\]](#)
44. Schnitzer, R.; Hapfelmeier, A.; Gaube, S.; Zillner, S. AI Hazard Management: A Framework for the Systematic Management of Root Causes for AI Risks. In *Frontiers of Artificial Intelligence, Ethics, and Multidisciplinary Applications*; Farmanbar, M., Tzamtzi, M., Verma, A.K., Chakravorty, A., Eds.; Springer: Singapore, 2024. [\[CrossRef\]](#)
45. Speiser, J.L.; Miller, M.E.; Tooze, J.; Ip, E. A comparison of random forest variable selection methods for classification prediction modeling. *Expert Syst. Appl.* **2019**, *134*, 93–101. [\[CrossRef\]](#)
46. Mehdiyev, N.; Fettke, P. Explainable Artificial Intelligence for Process Mining: A General Overview and Application of a Novel Local Explanation Approach for Predictive Process Monitoring. In *Interpretable Artificial Intelligence: A Perspective of Granular Computing*; Pedrycz, W., Chen, S.M., Eds.; Studies in Computational Intelligence; Springer: Cham, Switzerland, 2021; Volume 937. [\[CrossRef\]](#)
47. Campana, P.; Censi, R.; Tarola, A.M.; Ruggieri, R. Artificial Intelligence and Digital Twins for Sustainable Waste Management: A Bibliometric and Thematic Review. *Appl. Sci.* **2025**, *15*, 6337. [\[CrossRef\]](#)
48. Campana, P.; Censi, R.; Ruggieri, R.; Amendola, C. Smart Grids and Sustainability: The Impact of Digital Technologies on the Energy Transition. *Energies* **2025**, *18*, 2149. [\[CrossRef\]](#)
49. Censi, R.; Campana, P.; Tarola, A.M.; Ruggieri, R. Digital Pathways Toward Sustainability in Agri-Food Waste: A Systematic Review. *Resources* **2025**, *14*, 126. [\[CrossRef\]](#)
50. Bellini, F.; Campana, P.; Censi, R.; Di Renzo, M.; Tarola, A.M. Energy Communities in the Transition to Renewable Sources: Innovative Models of Energy Self-Sufficiency through Organic Waste. *Energies* **2024**, *17*, 3789. [\[CrossRef\]](#)
51. Seow, R.Y.C. Transforming ESG Analytics with Machine Learning: A Systematic Literature Review Using TCCM Framework. *Corp. Soc. Responsib. Environ. Manag.* **2025**, *32*, 7358–7389. [\[CrossRef\]](#)
52. Al Qudah, S.M.A.; Fuentes Bagues, J.L.; Ferrer Gisbert, P.; Al-Abdallat, H.N. AI-Driven Risk Management to Promote SDGs? An Exploratory Study in Jordan Construction Sector. *Sustain. Dev.* **2025**, *33*, 1107–1123. [\[CrossRef\]](#)
53. Cruz, P.L.; Ávila, L.V.; Pimenta Dinis, M.A.; Baggio, D.K. Environmental, social and governance (ESG) and innovation in the construction sector: Systematic Literature Review. *Rev. Adm. UFSM* **2023**, *16*, 1–38. [\[CrossRef\]](#)
54. Kwilinski, A.; Lyulyov, O.; Pimonenko, T. The role of green finance in attaining environmental sustainability within a country's ESG performance. *J. Innov. Knowl.* **2025**, *10*, 100674. [\[CrossRef\]](#)
55. Xiong, M.; Xu, H.; Ji, J.; Zuo, R.; Wang, Y.; Olya, H. Responsible Artificial Intelligence Attention and Firm Innovation: An Attention-Based View. *J. Prod. Innov. Manag.* **2025**, *early view*. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.