An adaptive AI-MCDM framework for sustainability assessment in construction projects

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Abstract. The construction sector is a significant producer of greenhouse gas emissions and depletors of natural resources, but its application of sustainability assessment is fragmented and separate from the use of computerized tools for managing building and construction projects. In this study, an adaptive AI-enhanced multiple criteria decision making (MCDM) framework that integrates expert opinions and recalibrates a neural network using a multilayer perceptron (MLP) has been developed. Also, the framework includes explainable AI via SHAP analysis and benchmarking of results to international standards (LEED, BREEAM, and DGNB). Three construction projects in Albania were selected to test the framework; Project A and Project B obtained sustainability scores of 0.825 and 0.813, respectively, and both exceeded the lowest global threshold. However, Project C achieved a score of 0.447 and indicated structural issues in achieving sustainability. Results of SHAP analysis showed that the two most important factors influencing sustainability were the reduction in CO2 emissions (up to 38% of total environmental weight post-AI recalculation) and cost efficiency. Compared to static weights, the AI-enhanced model decreased deviations from international standards by approximately 15%. A sensitivity analysis and a series of Monte Carlo simulations provided evidence of the robustness of the methodology, where changes to project ranking did not exceed 3%. Thus, this method will assist construction managers and policy makers to develop sustainable assessment methods that can be integrated into digital applications.

1 Introduction

The construction industry has experienced tremendous transformation globally; however, it remains a major contributor to environmental degradation, primarily due to its carbon footprint, urban waste generation, and resource utilization [1].

Rapidly expanding infrastructure and housing construction in developing economies continue to exert intense pressure on achieving sustainability objectives. At the same time, the construction industry is undergoing a massive shift with respect to how it conducts business, largely driven by digitalization. Industry 4.0 is rapidly integrating various

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technologies (i.e., BIM, Digital Twins, IoT, Artificial Intelligence, Big Data Analytics) into daily project practices in the construction industry [2]. These tools can be used to improve the project life cycle, make it more efficient and accurate, improve material selection, estimate cost, energy performance and plan the project. But, despite digital advancement, sustainability assessment often remains manual and fragmented, which shows that the full implementation of technologies in construction processes is necessary [3]. While the above digital technologies have shown great promise to support sustainable construction practices [4][5], there has been very little research or implementation of integrating digital technologies into sustainability assessment frameworks. The literature review section (section 2) outlines in detail many of the current sustainability assessment approaches used in building design and construction, which utilize static expert-assigned weights and do not function within the context of a digital work environment. These two limitations of existing approaches include (1) an inability to revise assessment criteria based upon evolving project conditions, and (2) the lack of connection between sustainability assessments and BIM-based platforms where daily project decisions occur [3]. This study bridges this gap by providing a hybrid AI-MCDM framework that can adapt to changing project conditions and be integrated directly into digital construction platforms.

This research has made three major contributions. The first is that this research will contribute to an ongoing improvement in the present MCDM method through a combination of a professional assessment along with an AI- enhanced recalibration of sustainability indicators. The second contribution is that the model is applied to Albanian construction projects, which provides evidence of the usefulness of the model as a decision-making support tool for construction projects. The third contribution is that it fills the lack of AI-MCDM methods in the Western Balkans by providing one of the first empirical studies of this type in the region. In addition to this, the study will help to bridge the gap between scientific research and the practical use of the assessments developed through this study by providing construction industry professionals and policy makers with a method for assessing the sustainability of their projects. The paper begins with a description of recent developments in both the digitalization of construction processes and in the area of sustainability assessment. It then provides an overview of the proposed methodology, which utilizes AI and MCDM to automate the sustainability assessment process. The results of this study are then described in terms of the role that automation plays in integrating with BIM platforms and digital twins. The study concludes with a summary of the main findings of this study, a description of the study's limitations, suggestions for how the methodology can be used in practice, descriptions of policies that should be developed to support the use of the methodology, and descriptions of the possibilities for future research.

This paper contributes one of the first real-world applications of a framework for Digital Innovation in the Western Balkan region (Albania) by providing evidence that Digital Innovation can be a major contributor to the long-term viability of both project implementation and urban development. In the subsequent sections, we will provide an overview of current literature on three inter-related themes: the role of Digital Transformation in supporting sustainable construction practice; the application of Multiple Criteria Decision Making (MCDM) techniques as tools to evaluate the sustainability performance of buildings; and recent developments regarding the potential uses of Artificial Intelligence to improve the accuracy and flexibility of MCDM evaluations.

2 Literature Review

2.1 Digital Transformation and Sustainability in Construction

Digitalization is affecting all segments of the construction sector at a very fast rate. Digitalization is changing how most of the construction industry operates today at an extremely rapid pace. Digitalization in the construction industry started with the development of computer-aided design (CAD) in the 1990s; progressed to building information modeling (BIM) in the 2000s; and now continues into Industry 4.0 with the integration of artificial intelligence (AI), Internet of Things (IoT), and digital twin capabilities to monitor in real time and provide predictive analytics [2]. In addition, as digitalization in the construction industry has evolved, so too have the perspectives on sustainability. The perspectives on sustainability have moved from solely focusing on environmental aspects to include economic, social, and technological aspects [1]. Construction projects such as residential, commercial, infrastructure and industrial each present unique sustainability challenges that require different approaches. As an example, BIM, Digital Twins, IoT and big data are no longer experimental tools to be used in a project's planning phase, but rather are now integral parts of every project's ongoing monitoring and management process. The benefits of digitalization are greater than simply making construction processes more efficient. Digitalization also integrates sustainability into the construction process during all phases, including planning, implementation and monitoring. Sustainability has been integrated into the construction process through the use of BIM (Building Information Modeling) and digital twins. BIM brings together all of the design, planning and performance information. A digital twin gives a continuous flow of information on how much energy a building is using, the building's carbon footprint, etc., [6]. In addition to that, with AI now being incorporated in day-to-day construction activities, teams can better plan their material needs, keep their cost in check and also consume less energy. This clearly indicates that the construction sector has been rapidly moving towards Industry 4.0 [2]. However, despite the digitalization that is occurring in the construction sector, sustainability assessments continue to remain highly manual and fragmented, and thus have limited integration with digital platforms where major project decisions are being made [3].

Most of the platforms that exist today have a focus primarily on efficiency and cost. When environmental and social factors are included, these tend to be merely "added-on" to BIM panels and/or twin system applications and not truly integrated into the BIM panels or twin systems themselves. Additionally, they are rarely compatible with internationally recognized global sustainable standards for buildings (i.e. LEED, BREEAM, etc.), which makes it difficult to compare projects across different geographies and therefore reduces their global adoption [7]. Overall, this highlights a clear gap in current practice, since while digital tools can measure/report performance, they currently cannot provide full support for assessing sustainability in a completely integrated/automated method. Also, due to the lack of interoperability among the various platforms, the integration process is both time-consuming/costly and technically complicated. These systems require considerable amounts of time and effort and often require specific technical skills; however, these may not be readily available in developing economies. At the same time, many of the proposed solutions remain at experimental stages, with no clear evidence of their successful implementation at scale. The increased attention of researchers in developed regions creates a clear gap in the literature regarding contexts where infrastructure is expanding at a rapid pace. Different studies in Automation in Construction show that AI, BIM and digital twins have indeed the potential to improve greatly how projects are planned, designed and managed. [4] Meanwhile, sustainability is often treated only as an environmental issue, without including other important dimensions, such as affordability, resilience, and community well-being. In this regard, sustainability risks remain just a slogan, not a real, practical objective.

The way digital technologies manage project monitoring & management has already altered many ways; however, as yet, the evaluation of project sustainability continues to lag. To date, research studies have generally focused on the efficiency of process execution (and not the production of a fully automated, comprehensive, or integrated framework for BIM), thus closing this gap is the purpose of this study. The proposed approach will provide a tool with which to easily automate sustainability aspects and adapt to various project types, and be important at either the local or global levels.

2.2 Multi-Criteria Decision-Making (MCDM) in Construction Sustainability

Over the past twenty years, MCDM methods such as AHP, TOPSIS, and fuzzy logic have become important tools in construction research [8]. They are increasingly used to support decision-making in situations where different and often competing priorities must be balanced. In the early stages of projects, these methods have been applied in processes where decisions have long-term impacts, such as life cycle analysis and risk assessment [9]. The implementation of these methods in practice is not simple. The reliance of these methods on fixed weights that experts give to the criteria, and the lack of flexibility to update in real time with the changes that occur in projects, make decision-making and responding to new challenges difficult. In most cases, evaluations are conducted separately from BIM panels or digital twin platforms, which limits their impact on the day-to-day management of projects.

The majority of the available data are based upon pilot projects or hypothetical cases, which may offer valuable insight into the use of alternative sustainability methods, they cannot demonstrate the efficiency of such methods in large-scale, evolving projects. It is difficult to determine whether these methods will be reliable and practical in the long-term without further validation. The ability to compare methods is also limited. Most studies do not measure their findings against established sustainability standards (i.e., LEED or BREEAM) [7]. When studies do not make these comparisons, it is extremely difficult to position the results within an internationally accepted framework, thereby limiting the ability to compare similar projects across different geographic locations. In addition to reducing the applicability of the study's findings, the absence of comparative analysis represents a disparity between academic research and global practice. The literature has shown that MCDM can play a critical role in assisting decision-making in construction by using MCDM in conjunction with BIM systems and digital twin platforms[5]. Although MCDM is capable of being used effectively to support decision-making in construction, most previous attempts to apply MCDM to assist decision-making in construction have primarily addressed technical aspects and were conducted at the testing phase. Very few studies of MCDM have demonstrated practical applications and, therefore, a broader spectrum of sustainability issues, such as affordability and community well-being, are frequently overlooked. Therefore, additional flexibility is required in MCDM methods to address project-based realities, so that they may serve as effective tools to facilitate decision-making in professional practice.

2.3 Artificial Intelligence in Construction Sustainability Evaluations

Construction project sustainability evaluation will be improved through an increasing application of Artificial Intelligence (AI) as a tool for evaluating sustainability. AI facilitates a much more dynamic approach to evaluating sustainability than static methods by allowing indicators to evolve with the changing needs of the project. Additionally, AI enables more reliable predictions of project performance and enables decision makers to make those decisions with increased confidence. The use of several techniques, such as Neural Networks, Regression Models and Genetic Algorithms, has already been utilized in many different areas, including the prediction of future energy consumption and optimization of construction scheduling processes [10]. Recent studies using Natural Language Processing have taken this a step further by demonstrating how AI can extract and analyze data from non-structured sources, such as project reports, contract documents and regulatory documentation [10].

Despite these advances, important challenges remain. Many AI applications function as "black boxes," offering results that are difficult for practitioners to understand or fully trust [11]. Techniques that make AI more transparent and explainable are still rarely used in sustainability evaluations, even though they are essential if such tools are to be accepted by industry professionals. Another limitation is that most applications tend to focus on narrow issues, for example, improving energy performance, while leaving aside the broader view of sustainability that also includes economic and social concerns. So far, the use of AI within the digital systems that are now common in construction has been quite limited. Only a small number of studies have tried to connect AI with tools such as Building Information Modeling (BIM) or digital twins, and these attempts have mostly been carried out in advanced economies where the level of digitalization is already high [6]. Much less is known about how these approaches could work in emerging economies, where construction is expanding quickly but where budgets are tighter, and sustainability challenges are often more severe. The literature shows that digital tools, MCDM, and artificial intelligence are developing in parallel, but not in an integrated manner.

Currently, the improvement of efficiency and the reduction of environmental impact are at the centre of attention, while, despite the role of equally important issues in urban development, such as affordability, resilience, governance, and community well-being, these have been transferred to the background. This is the gap that this study aims to fill, through a practical case from the Western Balkans.

3 Methodology

The study applies a hybrid approach based on the combination of Artificial Intelligence (AI) and Multi-Criteria Decision-Making (MCDM) to evaluate the sustainability of construction projects in Albania. It is a five-phase process in which all phases are interconnected with each other, starting with the selection and compilation of key sustainability indicators in relation to the literature review and contextual relevance. The next stage of the process involves conducting an Expert Consultation Phase to evaluate the indicators through practical knowledge and expertise related to this area of study. In the subsequent phase, a Multiple Criteria Decision-Making (MCDM) Technique is applied to aggregate and rank the results of the sustainability performance analysis from the different projects by using statistical methods such as Principal Component Analysis (PCA), Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Following that, the results are processed preliminarily and transformed into structured input data for the Artificial Intelligence (AI) System. Finally, the results of the sustainability performance analysis are predicted for the actual project by applying the AI model to the actual project data, so that the resulting predictions may have intelligence that could be useful in making decisions. These five stages of the methodology are presented schematically in the graphic illustration of the methodology in Figure 1 below, which illustrates the graphical representation of each process of the methodology and its contributions to the integrated AI – MCDM methodology.

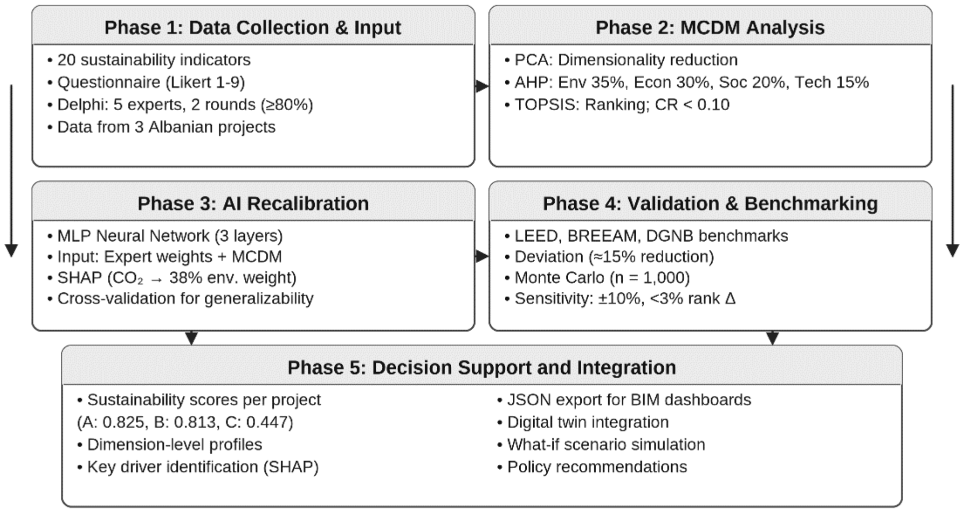

Fig. 1. Hybrid AI-MCDM framework for sustainability assessment

3.1 Expert-Based Data Collection and Project Sampling

Obtaining first-hand experience of the construction industry in Albania through collecting direct evidence from professionals with extensive experience in the field was necessary for developing a meaningful framework for assessing sustainability in this sector. A structured questionnaire was therefore developed, and interviews were carried out with experienced professionals who have been involved in the design, implementation and delivery of three large-scale construction projects in Albania. The three selected projects represented three different types of construction projects; they were selected so as to provide a wide view of the current state of sustainability practice. Five experts (a Project Manager, Finance Director, Environmental Engineer, Human Resources Representative, and Construction Technology Specialist) assessed each of the three selected projects throughout their entire life-cycle; the selection of these five experts provided a comprehensive evaluation of each project throughout its various stages of development. While there was agreement among the experts that financial constraints forced the revision of environmental goals of the projects, there was less consensus regarding the use of technical solutions applicable to the projects and the potential for enhancing social performance through the inclusion of local communities, similar to the findings of previous research. The sample size for this study is small (only 3), but they were selected because of their significance and professional commitment, and to prioritize quality over quantity of data. The number of experts, i.e., 5, is also in line with the recommendations made for the number of participants in a Delphi study, which suggests that the panel should comprise 5-10 specialists in order to conduct focused, domain-based assessments [12]. Expertise in each of the 4 sustainability areas was chosen as the basis for selecting the experts. To be eligible, an expert had to have at least 10 years of work experience and to have been involved in no less than two large-scale construction projects in Albania. The Project Manager (15 years) was responsible for overseeing the completion of the project; the Finance Director (12 years) assisted in determining costs; the Environmental Engineer (10 years) determined whether environmental regulations were being followed; the Human

Resource representative (11 years) determined the social impacts of the project; and the Construction Technology Specialist (13 years) determined how effectively the digital tools being used were adopted into practice. The diversity of disciplines helped ensure that all four sustainability dimensions were evaluated from the perspective of professionals who had extensive first-hand experience of practicing in this area. This greatly reduced the potential for subjective bias.

3.2 Indicator Weighting and Survey Design

These Sustainability Indicators were chosen using a combination of Theory & Practical Considerations, Literature Review and Sustainability Standards (such as LEED, BREEAM and ISO 21929) to establish commonality for International Sustainability Standards. Using these sources, the main Criteria were established and organized in Four Dimensions: Economic, Environmental, Social and Technical. These criteria were adapted to the Albanian Context through the use of a Delphi Process, involving five Experts in different Disciplines: Construction Project Management, Environment, Finance, and Intelligent Building Technologies. Each Dimension is comprised of two to three Sub-Indicators, bringing the total number of indicators to eleven. It should be noted that an initial pool of twenty candidate indicators was identified from the literature and international sustainability standards. Following Principal Component Analysis (PCA) for dimensionality reduction in Phase 2, indicators with high intercorrelation or low explanatory power were consolidated, resulting in the final set of eleven indicators used in the assessment.

The Indicators themselves, along with Definitions and Preliminary Weights, are shown in Table 1 as agreed by the Expert Panel.

Table 1. Sustainability Indicators and Weight Assignments [adapted from 1, 6, 9]

Category	Weight	Sub-Indicators	Description
Economic	0.30	Cost Efficiency	Measures effective cost management, ensuring financial feasibility and preventing cost overruns.
		Return on Investment (ROI)	Evaluates the financial returns relative to project costs, crucial for investors and stakeholders.
		Funding Availability	Assesses the ease of securing capital and the financial stability of the project.
Environmental	0.35	CO_2 Emission Reduction	Quantifies the reduction in greenhouse gases emitted during construction and operation.
		Use of Renewable Energy	Measures the extent to which the project incorporates renewable energy sources such as solar or wind power.
		Waste Management Systems	Evaluates the efficiency of waste handling, including recycling and disposal strategies.
Social	0.20	Job Creation	Measures the project's employment potential, including both direct and indirect job opportunities.
		Community Impact	Assesses how the project affects local communities in terms of accessibility,

			displacement, or improvement in living conditions.
		Affordable Housing	Evaluates whether the project contributes to providing cost-effective housing solutions for the population.
Technological	0.15	Smart Energy Management	Assesses the integration of intelligent energy systems to optimize consumption and reduce waste.
		Digital Construction Technologies	Measures the adoption of advanced digital tools such as Building Information Modeling (BIM), automation, and AI-driven monitoring.

Utilizing this steering panel as a guideline, we have developed our weighing and evaluation process with the suggested indicators for our indicator framework. The combination of expert knowledge with globally recognised standards of sustainability has ensured each indicator is appropriate to the context and is methodologically correct. This four-dimensional approach will allow us to evaluate the complete sustainability performance of all construction projects across four key areas; Environment, Economy, Society and Technology.

Before sending out the questionnaire, we carefully analyzed the most trusted international sustainability standards, such as LEED, BREEAM, and some ISO guidelines. But, knowing the importance of practice, we also spoke with professionals who manage projects, budgets, the environment, staff, and construction technologies every day. Based on expert judgment but also relying on the best international practices, a weighting system was established for the sustainability indicators: 35% for the environment, 30% for the economic aspect, 20% for the social dimension, and 15% for technology. The weight distribution for these three aspects (environmental, economic and social) is consistent with well-established sustainability assessment frameworks. The environmental weight of 35 % was based on the typical percentage allocation to environmental considerations in LEED/BREEAM assessments, where environmental considerations generally make up 30-40 % of the overall assessment [7]. The economic weight of 30 % was based on the need for financial viability in developing countries [1]. The social weight of 20 % was supported by recent studies that identified job creation and community impact as major drivers of sustainable development [8]. The technological weight of 15 % was based on the current stage of digital adoption in the Albanian construction industry [6]. The weighting scheme was validated by two Delphi rounds in which there was an average agreement of 80 % amongst the five experts [12].

3.3 AI-Based Weight Optimization

An MLP regressor was used (in Python) with the support of scikit-learn to collaborate with professionals' (experts') judgment on actual project data. It was intended to serve the needs of the professionals by displaying hidden trends rather than replacing their expertise. The AI model demonstrated an improvement in the weights given by professionals in relation to environmental factors' influence on sustainability results, where there are repeated environmental factors influencing the sustainability results more so than the professionals believed existed. This was done with an emphasis on maintaining all dimensions in balance. In summary, this analysis combines both evidence based on the data with the professional's (expert's) knowledge. The model was repeatedly trained and tested with standard accuracy metrics to provide assurance that the results were consistently valid every time it was tested. Cross-validation techniques were applied to ensure the generalizability of the model [13].

The consistent test results were a good indicator of the model's reliability as a tool to assess sustainability within real-world construction projects.

We tested the framework in three different ways. The first relied only on the weights defined by experts. In the second approach, AI calibration was introduced, though no feedback was applied. The third approach combined AI calibration with a feedback loop and explainable AI, which worked better. It brought the results closer to international standards such as LEED and BREEAM, produced outcomes that were more consistent with global sustainability standards, and reduced error rates compared with the other two configurations. The gradual evolution of the weights in line with the changes that occur in the project constitutes the novelty of this study.

Finally, in order to maintain the system transparent and easy to use by practitioners, we used explainable AI techniques. SHAP values, for example, made it clear which indicators had the greatest impact on the results. Across all three projects, the most important factors proved to be the reduction of carbon emissions and the control of costs [14]. In Project B, what really stood out was its strong commitment to renewable energy, while in Project C, the most meaningful contribution came from its capacity to create new jobs. Figure 2 demonstrates the contribution of important indicators using SHAP values.

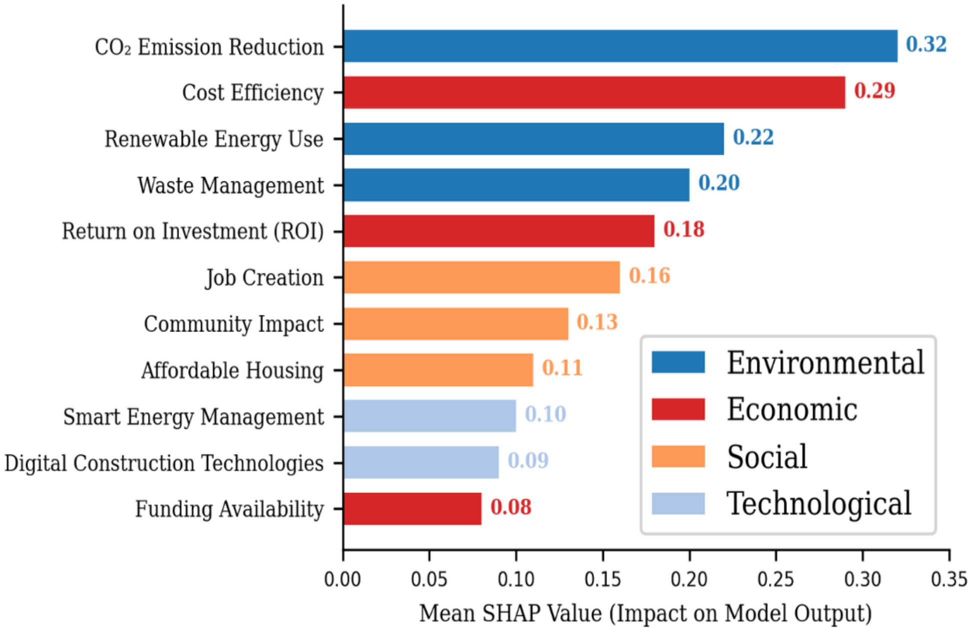

Fig. 2. SHAP analysis of sustainability indicator importance

The use of established International Frameworks added a further layer of assurance to the results generated by our model. In addition to our own analysis, when we applied our results to other well-established systems (LEED, BREEAM, DGNB), the AI-enhanced version of the model produced far better correlation with those systems than the static weighting models. On average, the AI-enhanced model resulted in a 15% reduction in the difference between our results and the existing benchmarks. As a result, this indicates that the methodology is both sensitive to the unique characteristics of each project and also consistent with the standards universally accepted across the world.

In order to test how reliable the model was, we carried out sensitivity checks and Monte Carlo simulations with one thousand test runs. Even when we introduced small variations in the indicator scores, the overall project rankings shifted by less than three percent [15]. We

also examined three possible scenarios described as optimistic, baseline, and pessimistic. The findings demonstrated that the adaptive AI system was able to change the weights consistently and not be locked to a profile of a particular project.
Our hybrid method achieved a better balance compared to traditional approaches such as AHP and TOPSIS [9]. In the tables that follow, we show how this process worked. Table 2 compares the original weights provided by experts with the updated AI-informed values for Project A.

Table 2. Weight Optimization for Project A

Indicator	Expert Weight	AI-Optimised Weight	Average Sub-Score	Result (Expert Weight)	Result (AI Weight)	Difference
Economic	0.30	0.28	0.80	0.80 × 0.30 = 0.240	0.80 × 0.28 = 0.224	-0.016
Environmental	0.35	0.38	0.90	0.90 × 0.35 = 0.315	0.90 × 0.38 = 0.342	+0.027
Social	0.20	0.18	0.75	0.75 × 0.20 = 0.150	0.75 × 0.18 = 0.135	-0.015
Technological	0.15	0.16	0.80	0.80 × 0.15 = 0.120	0.80 × 0.16 = 0.128	+0.008
Total Score				0.825	0.829	+0.004

Table 3 presents a summary of the revised outputs from Project B. It compares the weights assigned to each dimension by the experts with those artificially generated (via AI), as well as illustrates the variation between them. There was little alteration among economic and social dimensions; however, there was a large increase in weight to the environmental factor, which further solidified its position as the primary component within the project's sustainability.

Table 3. Weight Optimization for Project B

Indicator	Expert Weight	AI-Optimised Weight	Average Sub-Score	Result (Expert Weight)	Result (AI Weight)	Difference
Economic	0.30	0.29	0.78	0.78 × 0.30 = 0.234	0.78 × 0.29 = 0.226	-0.008
Environmental	0.35	0.37	0.88	0.88 × 0.35 = 0.308	0.88 × 0.37 = 0.326	+0.018
Social	0.20	0.19	0.74	0.74 × 0.20 = 0.148	0.74 × 0.19 = 0.141	-0.007
Technological	0.15	0.15	0.82	0.82 × 0.15 = 0.123	0.82 × 0.15 = 0.123	0.000
Total Score				0.813	0.816	+0.003

In Project B, there was an even greater emphasis on environmental factors than there was in Project A, reinforcing the idea that environmental factors have a significant influence on sustainability results. In contrast with Project A, the technology factor did not exhibit changes, which is consistent with how slowly this project adopted new technologies and practices. The artificial intelligence model adjusts its weights based on the sustainability attributes of each project. For example, the AI adjustments for Project C were specifically designed to take into consideration the particular sustainability issues of the project so as to provide an evaluation of the project's sustainability that was more accurate and unbiased (see Table 4).

Table 4. Weight Optimization for Project C

Indicator	Expert Weight	AI-Optimised Weight	Average Sub-Score	Result (Expert Weight)	Result (AI Weight)	Difference
Economic	0.30	0.29	0.45	0.45 × 0.30 = 0.135	0.45 × 0.29 = 0.131	-0.004
Environmental	0.35	0.36	0.40	0.40 × 0.35 = 0.140	0.40 × 0.36 = 0.144	+0.004
Social	0.20	0.18	0.50	0.50 × 0.20 = 0.100	0.50 × 0.18 = 0.090	-0.010
Technological	0.15	0.17	0.48	0.48 × 0.15 = 0.072	0.48 × 0.17 = 0.082	+0.010
Total Score				0.447	0.447	0.000

While both Projects A and B saw marginal increases in their AI-optimised total scores (Project A: +0.004, from 0.825 to 0.829; Project B: +0.003, from 0.813 to 0.816), Project C's total score was essentially unchanged, continuing to be 0.447 after recalculation; though the recalculation did result in a slight reduction in the social dimension weight, and a very slight increase in the weight of the technological dimension. By way of summary, Figure 3 illustrates that AI can't fix all of the major economic and environmental issues on its own. While A and B were able to achieve most of their sustainability due to high marks on the environmental dimension, Project C had much greater reliance on social and technological dimensions and achieved little by way of improving those areas. This demonstrates how the model adjusts to each specific project and identifies where efforts are needed to improve performance.

While all three cases (Projects A, B, and C) demonstrated AI-calibration based upon their unique individual projects, two very distinct features of these individual project types impacted the output of the framework: environmental conditions in both Projects A and B, and the pre-existing weaknesses that were present in Project C which ultimately negatively affected the overall outcome of Project C's use of the framework. Therefore, while the framework clearly offers many benefits and tools that can help identify areas of opportunity for improving performance as well as areas of risk in sustainable construction, it is still a dependent tool on the availability of quality and objective data from the specific projects that will be using the framework and also dependent on the reliability of the expert(s) that are providing the input required by the framework. The quality of the assessment provided by the framework can be increased when the assessment is done by multiple experts, since the reliability of expert judgments can be adversely affected by the presence of subjective influences in such assessments. While this paper provides evidence that the framework developed for this research can be effectively utilized in practice through the application of the framework to a real-world case study from Albania, additional applications of the framework are necessary in order to fully assess its effectiveness and potential at larger scales of application. Before this research, no other study has integrated AI, SHAP analysis, sensitivity checks, and international standards into a single tool used to examine sustainable construction in the Western Balkans; therefore, the integration demonstrated in this study indicates that the framework developed is more than simply an academic contribution and can also be a useful tool for supporting the daily activities of both construction companies and regulatory bodies.

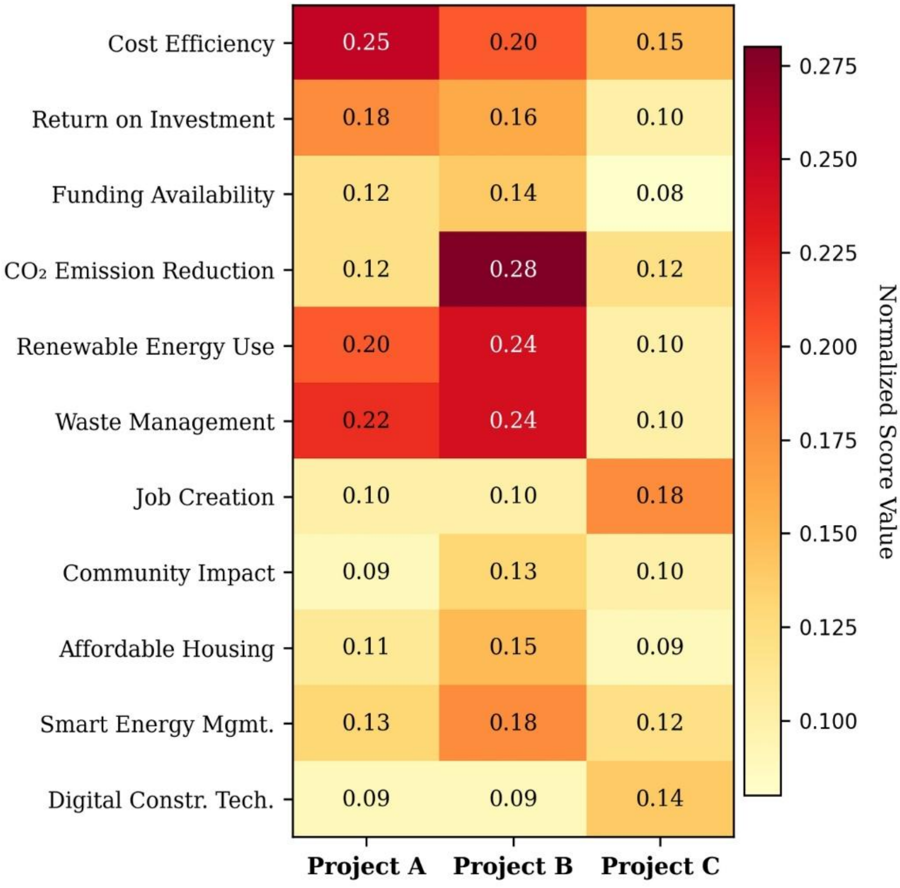

Fig. 3. Sustainability dimensions after AI recalibration

3.4 Integration with MCDM & Dynamic Feedback

After the weighting optimization using the AI, the sustainable performance indicators' final results were generated by integrating the recalibrated weights into the multi-criteria decision-making (MCDM) framework. Sustainability assessment of each project was conducted by the weighted aggregation of economic, environmental, social, and technological dimensions. The use of both expert judgment and AI-based weighting provided sustainable and well-balanced results. The results of sustainability assessments may also be updated if there is a need to change the priorities of sustainability. Furthermore, the framework may be linked to

Building Information Modelling (BIM) and project management dashboards; this will enable decision-makers to evaluate various alternatives and assess the impact of policy intervention. The adaptability of the framework enables it to transition from being a tool for evaluating sustainability to support decision-making processes.

A sensitivity analysis was used to verify the robustness of the framework. Variations of ±10% were introduced into the weights of indicators. The results indicated that the ranking of projects remained relatively unchanged, with less than a 3% variation, confirming that the model is reliable and can tolerate minor changes. Additionally, the results were compared against some minimal global standards, i.e., a reduction in CO_2 emission of 10%, and a rate of 15% for the use of renewable energy. [7] These comparisons ensure that the results are applicable internationally. Both Projects A and B exceeded the minimum requirements for the global standards; the most significant contributions to their results came from the environmental dimension. Project C, however, did not meet these minimum global standards, which indicates that it requires improvements. In addition to guiding the reader to better understand the evaluation of each indicator, the application of the weights, and the generation of the final sustainability results, Tables 1-7 provide additional information regarding the evaluation of each project. Specifically, Project A (see Table 5) demonstrated very strong results. The total score of Project A consisted of 35% from environmental factors, 30% from economic factors, 20% from social factors, and 15% from technological factors. This project was particularly unique due to the balance between financial management and sustainability, and demonstrates how fiscal responsibility and environmental responsibility can complement each other.

Table 5. Detailed Sustainability Evaluation for Project A

Category (Weight)	Sub-Indicator	Sub-Indicator Score	Calculation
Economic (0.30)	Cost Efficiency	0.82	(0.82 + 0.78 + 0.80)/3 = 0.80 ⇒ 0.80 × 0.30 = 0.240
	Return on Investment (ROI)	0.78	
	Funding Availability	0.80	
Environmental (0.35)	CO_2 Emission Reduction	0.92	(0.92 + 0.88 + 0.90)/3 = 0.90 ⇒0.90 × 0.35 = 0.315
	Use of Renewable Energy	0.88	
	Waste Management Systems	0.90	
Social (0.20)	Job Creation	0.70	(0.70 + 0.80 + 0.75)/3 = 0.75 ⇒ 0.75 × 0.20 = 0.150
	Community Impact	0.80	
	Affordable Housing	0.75	
Technological (0.15)	Smart Energy Management	0.80	(0.80 + 0.80)/2 = 0.80 ⇒ 0.80 × 0.15 = 0.120
	Digital Construction Technologies	0.80	
Final Score			0.240 + 0.315 + 0.150 + 0.120 = 0.825

In addition to being heavily impacted by Environmental, Economic, Social and Technological factors in Project B, each of these had a major impact on the Project as well. This project was particularly noted for its strong environmental focus and the positive effects that the project had on the local community (i.e., in terms of how people perceived the project and what benefits were generated for them). In spite of the fact that there were several challenges encountered in managing costs for the project and using advanced technology in the construction industry, the detailed sustainability assessment for Project B is illustrated in Table 6 below, and illustrates the contributions from the Environmental, Economic, Social, and Technological components.

Table 6. Detailed Sustainability Evaluation for Project B

Category (Weight)	Sub-Indicator	Sub-Indicator Score	Calculation
Economic (0.30)	Cost Efficiency	0.80	$(0.80 + 0.75 + 0.79)/3 \approx 0.78 \Rightarrow 0.78 \times 0.30 = 0.234$
	Return on Investment (ROI)	0.75	
	Funding Availability	0.79	
Environmental (0.35)	CO_2 Emission Reduction	0.90	$(0.90 + 0.85 + 0.89)/3 \approx 0.88 \Rightarrow 0.88 \times 0.35 = 0.308$
	Use of Renewable Energy	0.85	
	Waste Management Systems	0.89	
Social (0.20)	Job Creation	0.72	$(0.72 + 0.76 + 0.74)/3 = 0.74 \Rightarrow 0.74 \times 0.20 = 0.148$
	Community Impact	0.76	
	Affordable Housing	0.74	
Technological (0.15)	Smart Energy Management	0.83	$(0.83 + 0.81)/2 = 0.82 \Rightarrow 0.82 \times 0.15 = 0.123$
	Digital Construction Technologies	0.81	
Final Score			$0.234 + 0.308 + 0.148 + 0.123 = 0.813$

Project C was much weaker than Projects A and B on all dimensions, with no significant achievement in either an economic or environmental aspect, compared to minimal positive results in the social and technology dimension and those positive results being unable to compensate for the low financial feasibility and lack of ambitiousness environmentally. This is an example of how, although AI recalibrations may be able to change weights and emphasize the key components of a project, they are unable to overcome the fundamental structural weakness of a project which lacks the foundation of sustainability.

Table 7. Detailed Sustainability Evaluation for Project C

Category (Weight)	Sub-Indicator	Sub-Indicator Score	Calculation
Economic (0.30)	Cost Efficiency	0.50	$(0.50 + 0.40 + 0.45)/3 = 0.45 \Rightarrow 0.45 \times 0.30 = 0.135$
	Return on Investment (ROI)	0.40	
	Funding Availability	0.45	
Environmental (0.35)	CO_2 Emission Reduction	0.42	

	Use of Renewable Energy	0.38	(0.42 + 0.38 + 0.40)/3 = 0.40 ⇒ 0.40 × 0.35 = 0.140
	Waste Management Systems	0.40	
Social (0.20)	Job Creation	0.55	(0.55 + 0.50 + 0.45)/3 = 0.50 ⇒0.50 × 0.20 = 0.100
	Community Impact	0.50	
	Affordable Housing	0.45	
Technological (0.15)	Smart Energy Management	0.50	(0.50 + 0.46)/2 = 0.48 ⇒ 0.48 × 0.15 = 0.072
	Digital Construction Technologies	0.46	
Final Score			0.135 + 0.140 + 0.100 + 0.072 = 0.447

Projects A and B demonstrated a significant ability to exceed the lowest possible Global Sustainability Thresholds, especially regarding their Environmental Performance; however, Project C was unable to do so. The comparison demonstrates how difficult it can be for an organization to develop long-term sustainable practices if they lack strong Economic and Environmental foundations. Simultaneously, the results of the study illustrate that the framework has been able to do more than just provide a score.

4 Results

It is evident from the diverse perspectives of the three case studies that the flexibility of the AI MCDM framework allows for a wide variety of approaches to sustainability. In terms of the ability to find a balance between their environmental and financial dimensions, Projects A and B were successful in both realms. Conversely, in Project C, the inability to achieve success in the environmental dimension had a negative effect on the overall sustainability. Based on a review of the literature, environmental and economic issues constitute the majority of the weighted factors used in evaluating sustainability. Social and technological factors support the environmental and economic factors. Although the changes were relatively small (i.e., the increase in the weighting of environmental issues in Projects A and B), the models produced results that may have been difficult for the experts to determine without the use of the models. Recalibrating the weights in Project C demonstrated that the weakness in the environmental area, combined with the economic weakness, created an imbalance that could be balanced out by only modest advancements in other areas. The AI MCDM model does not create a false sense of what is sustainable; instead, it identifies the factors that actually contribute to sustainability. Using the SHAP analysis, the model identified CO_2 reduction and cost management as the primary drivers of sustainability. Renewable energy played a significant role in Project B, and job creation played a significant role in Project C. The gap between the model's evaluation of sustainability and these two standards decreased by approximately 15% when compared to static weights. This indicates that the model utilizes local data, but evaluates sustainability in accordance with international standards.

A sensitivity analysis was completed along with over 1,000 Monte Carlo simulations to demonstrate the stability of the model's ranking of projects. The simulations demonstrated that there was less than a 3% variance in all types of analyses (sensitivity analysis, etc.) [15]. As compared to previous methodologies such as AHP or TOPSIS, and/or to neural networks, this hybrid AI-MCDM model provides a superior compromise, being accurate, transparent and efficient. [9], [5].

5 Discussion

The developed model demonstrated a high level of stability during testing. As part of the sensitivity analysis and 1000 Monte Carlo runs on the model, it was found that even when the test cases changed, the project rankings rarely changed at all, with changes being less than 3% [15]. The development of the framework has gone beyond providing scoring systems for evaluating and ranking projects. In addition to aiding city officials and planners in their daily decision-making processes, the framework may assist them in identifying projects that do not meet sustainable criteria; for example, while they provide some reduction in greenhouse gas (carbon) emissions via the use of renewable energy sources, they achieve that goal with only minimum amounts of reduction.

Planners are able to examine alternative approaches, for example, by increasing building heights, and assess their possible sustainability impacts. Since the results can be exported in JSON format and used for real-time simulations, decision makers are allowed to anticipate the effects of changes before they are implemented. Although the empirical analysis was based on a limited number of projects and experts, the findings show that the framework maintains its robustness under different conditions.

5.1 Implications of the Study

The findings carry important implications across theoretical, practical, and policy dimensions. From a theoretical perspective, integrating AI-based weight recalibration with MCDM and explainable AI (SHAP) represents a methodological advancement over traditional static approaches. This allows sustainability indicators to be dynamically adjusted based on actual project performance. From a practical standpoint, the framework can be incorporated into BIM dashboards and digital twin platforms, enabling real-time sustainability monitoring. Construction managers can use the automated scoring tools to identify underperforming dimensions and take corrective action during the project lifecycle. For policy-makers and urban planners, the ability to export results in JSON format and simulate scenarios means sustainability assessments can be embedded into standard planning processes. For the Western Balkans specifically, this study demonstrates that AI-enhanced sustainability assessment is feasible even in data-limited environments, providing a replicable model for other developing economies.

6 Conclusion and Recommendations

This study developed a hybrid artificial intelligence and multi-criteria decision-making (AI-MCDM) framework to facilitate a more practical, flexible, and transparent approach to conducting sustainability assessments within the construction industry. The main findings and contributions are described below:

1. Performance of the Framework: The AI-enhanced model reduced the variance of the weights assigned to each sustainability indicator from the international standards (LEED, BREEAM, DGNB) by approximately 15%, while Monte Carlo simulations indicated that there was less than 3% variability in the ranking of projects using the AI-enhanced model.
2. Results of the Case Study: Both Project A (0.825) and Project B (0.813) were greater than the global sustainability threshold, which demonstrates that when a project

maintains financial discipline and preserves the environment at the same time, both goals can be achieved simultaneously. On the other hand, Project C (0.447) demonstrated the risk associated with poor cost control and inadequate environmental considerations.

3. Transparency through SHAP Analysis: The use of SHAP analysis to explain how the AI reached its conclusions demonstrated that the most significant sustainability indicators included reductions in CO_2 emissions (as much as 38% of the total environmental weight) and cost efficiency. Thus, the AI's recalculation process was completely understandable by those who will be using the AI to make decisions in the construction industry.
4. Contribution to the Body of Literature/Methodology: The combination of expert-based Delphi weighting, MLP neural network recalculation, and MCDM integration provides a repeatable method of conducting dynamic sustainability assessments in data-scarce environments.
5. Integration into Practice: The results of this study can be exported in JSON format, integrated into Building Information Modeling (BIM) dashboard displays, and simulated through digital twin technology, thereby allowing real-time decision-making assistance for project managers, regulatory agencies, and policymakers.
6. Regional Significance: This study represents one of the first empirical uses of AI-MCDM methods for conducting sustainability assessments in the Western Balkan region, and also demonstrates the potential for AI-MCDM methods to be used in emerging economies where there is limited digital infrastructure.
7. Limitations of the Study and Suggestions for Future Research: Although the results of this study are based upon three projects and five experts, future studies need to increase the number of cases and expand the pool of experts; also, future studies need to demonstrate a linkage between the predicted outcomes of the sustainability assessments and the actual post-construction performance of the assessed building; finally, future studies need to develop automated data pipelines so that the AI-MCDM methods can continuously monitor the sustainability performance of the assessed buildings over time.

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