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Evaluation of the Sustainable Development Goals in the Diagnosis and Prediction of the Sustainability of Projects Aimed at Local Communities in Latin America and the Caribbean

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Abstract: The purpose of this article is to help to bridge the gap between sustainability and its application to project management by developing a methodology based on artificial intelligence to diagnose, classify, and forecast the level of sustainability of a sample of 186 projects aimed at local communities in Latin American and Caribbean countries. First, the compliance evaluation with the Sustainable Development Goals (SDGs) within the framework of the 2030 Agenda served to diagnose and determine, through fuzzy sets, a global sustainability index for the sample, resulting in a value of 0.638, in accordance with the overall average for the region. Probabilistic predictions were then made on the sustainability of the projects using a series of supervised learning classifiers (SVM, Random Forest, AdaBoost, KNN, etc.), with the SMOTE resampling technique, which provided a significant improvement toward the results of the different metrics of the base models. In this context, the Support Vector Machine (SVM) + SMOTE was the best classification algorithm, with accuracy of 0.92. Lastly, the extrapolation of this methodology is to be expected toward other realities and local circumstances, contributing to the fulfillment of the SDGs and the development of individual and collective capacities through the management and direction of projects.

Keywords: SDGs; SMOTE; artificial intelligence; projects; fuzzy logic

1. Introduction

1.1. Sustainable Project Management

The concept of sustainable development appeared for the first time in 1987, following the publication of the United Nations Brundtland Report, which, among other issues, denounced the environmental impacts derived from the intensive use of natural resources in production activities [1].

The social policies and movements of the late 20th century led the term to acquire an economic dimension, beyond the purely environmental one, converging with the postulates of Corporate Social Responsibility (CSR), aimed at assessing the impact of business actions on society.

This meta-concept, called sustainability or the "Triple Bottom Line (TBL)", evaluates the creation of value in companies, distinguishing between the economic, social, and environmental spheres in their income statements [2].

The current paradigm shift represented by sustainability involves moving away from the here and now of CSR and evolving towards new models that last over time [3], which can be part of the strategic and operational processes of organizations through projects [4]. In this way, projects become a potential means of transmitting sustainable practices to local communities [5], promoting behavioral changes and delivering business value [6].

However, even though, in recent years, there has been an effort to incorporate sustainability in a cross-cutting manner into project management [7], there is a gap between the perception of the importance of sustainability and its actual use in project management practice [8].

According to Okland [9], one of the reasons stems from the ambiguity of the term and its multiple definitions, which cause confusion when applying it to project management, making the acquisition of competencies in this area essential for the project manager (Table 1).

Table 1. Basic descriptors to achieve a project manager's TBL competences during the evaluation stage.

Materials	TBL Descriptors
Project market	General aspects of the industry. Background study. Demand from potential clients. Entry barriers.
Project profitability	Social profitability vs. economic profitability. Compensation of monetary deficit. Subsidies, grants, and aids.
Social investment projects	Promotion of local development. Support for the traditions and rights of indigenous communities. Private vs. social evaluation.
Technology and environment in the project	Pollution prevention and control. Environmental risk management. Biodiversity preservation. Fight against climate change. Life cycle analysis. Environmental Impact Assessment. Compliance with legal or social regulatory requirements.
Project risk and uncertainty	Socioeconomic risk mitigation measures. Sensitivity analysis of sustainability projects.

Note. Own elaboration.

A significant example is the scarcity of sustainable criteria contained in the currently most accepted project norms and standards, such as IPMA ICB4® [10], PMBOK® [11], PRINCE2® [12], or the Guide for Project Management ISO 21500:2012 [8,13–15]. In this context, a sustainable approach is only seen in agile project methodologies, aimed at software development (Agile Methodologies), and in the PRISM methodology (Projects Integrating Sustainable Methods), which incorporates governance, environmental, economic, social, and technical factors from a set of good practices collected in different ISO standards [16].

On the other hand, both the PMBOK® Guides and ISO 21500:2012 continue to consider project management from a utilitarian view, i.e., focused exclusively on the outcome of the actions and, therefore, on the benefits of the project [9]. Along the same lines, Jeans et al. [17] allude to training to eradicate the dissonance implied by utilitarianism, in which the benefits resulting from the project are obtained only at the time of its execution [18], thus avoiding the durability over time of its actions. This perception of project management limits the introduction of sustainable criteria from very early stages, causing a misalignment from the point of view of local community stakeholders [19].

In this sense, because the effects of a project can last much longer than the project itself [9], sustainability in project management requires a governance framework—public or private—that is holistic and, therefore, focused on the early stages of project development, prior to making important decisions.

In short, there is no doubt about the importance of projects as an engine of change and a driving force for the development of local communities' capacities for the creation of sustainable value. However, the current utilitarian conception of the term, reflected in the economic instrumentalization and the gaps in norms and standards, envisions sustainability as an axiom that does not last throughout its life cycle.

It is therefore necessary to abandon non-holistic approaches and reduce the disconnection between sustainability and project management practices on local communities [20] to create the necessary conditions and develop the capacities of individuals through project management norms and standards.

1.2. Sustainability Evaluation Models in Project Management

Over the last two decades, numerous sustainability assessment models applied to project management have been developed [8]. Some of these models, such as those of Araujo [21], Macaskill and Guthrie [22], and Corder et al. [23], maintain a holistic view and incorporate sustainability within the project management process. However, other models, such as that of the OECD [24], conceive it as an outcome [9].

In any case, it is common in these models for the measurement to incorporate certain evaluation criteria beyond the traditional ones (scope, time, and cost), which use indicators of all kinds. For example, the OECD model employs criteria such as efficiency, effectiveness, impact, relevance, and sustainability, which use economic, environmental, social, and technological indicators in a cross-cutting manner, among others [9].

However, the models are scattered and, in general, incomplete, without a defined instrumentalization, making it very difficult to integrate them with the organization's idiosyncrasy and, consequently, taking advantage of the competitive edge in the market.

Using a quantitative method of priority scales based on expert judgement (AHP method), Martens and Carvalho [8], aware of this problem, identified and condensed the variables of the main sustainability models focused on TBL in the context of the management and success of projects in different areas of engineering and administration.

Table 2 shows the most highly valued indicators according to expert judgement and grouped by dimension.

Table 2. The most valued indicators of the different sustainability models of project management in the areas of engineering and administration, according to Martens and Carvalho.

Dimension	Number of Variables Identified	Indicators
Economic	158	Survival of the organization Cost management Stakeholder relations
Environmental	248	Employee welfare Air, water, energy, and soil Waste generation Material consumption Other *
Social	270	Good labor practices Community relations Child labor Human rights Impact of products and services Financing of social actions

Note. Adapted from Martens and Carvalho [8]. * It refers to compliance with legislation, global warming, noise, environmental policies, training, and environmental education.

Within the scope of this research, a model based on the Sustainable Development Goals (SDGs) was proposed to assess the sustainability of multi-sectorial projects. As we will see in the following section, no general sustainability assessment models incorporating the SDGs in project management have been found, except for isolated cases aimed at a specific sector.

In this context, the SDGs play a very important role in developing capacities at the local community level and breaking the traditional paradigm, by influencing issues such as gender perspectives, inequality reduction, and climate action, among others [25,26].

1.3. Sustainable Development Goals (SDGs) and Their Relation to Project Management

The Sustainable Development Goals (SDGs) were presented for the first time in 2015, during the United Nations Sustainable Development Summit, as the International Community's response to the challenges of climate change and sustainable development (Table 3). These 17 goals, to be achieved by all nations belonging to the UN General Assembly before 2030, are composed of a total of 169 targets and 232 indicators, supervised by a team of experts who report the data to a publicly accessible repository for the follow-up and monitoring of their implementation [20].

Table 3. List of Sustainable Development Goals (SDGs).

Number	SDGs	Number	SDGs
1	No poverty	10	Reduced inequalities
2	Zero hunger	11	Sustainable cities and communities
3	Good health and well-being	12	Responsible consumption and production
4	Quality education	13	Climate action
5	Gender equality	14	Life below water
6	Clean water and sanitation	15	Life on land
7	Affordable and clean energy	16	Peace, justice, and strong institutions
8	Decent work and economic growth	17	Partnerships for said goals
9	Industry, innovation, and infrastructure		

Note. United Nations [20].

In contrast to sustainable project management, the relationship between the SDGs and project success is a topic that has been rarely addressed in the literature [27]. Some authors allude to the lack of maturity of organizations in reflecting the impacts of the SDGs in their reporting [28], which in turn produces a knowledge gap, preventing the dissemination of project successes or failures [9].

An example that perfectly illustrates the challenge for project managers to include the SDGs in the project life cycle is the climate change phenomenon, which directly affects, to a greater or lesser extent, each of these goals [29].

In April 2022, the Intergovernmental Panel on Climate Change (IPCC) published the third mitigation part of its Sixth Assessment Report. One of the conclusions of this report was that, even though great efforts have been made in the last decade to reduce mitigation costs, especially for solar energy, there is still a considerable gap between current measurements and those needed to limit warming to 1.5 °C by 2030 [9,30].

This discrepancy with respect to national and global mitigation targets poses a challenge for project managers seeking to measure the impact of the SDGs, as it is very common for aspects such as time, cost, and quality to be highlighted, with less consideration being given to the environmental, social, and financial effects of the TBL.

In this sense, the influence of the financial factor in general and the proliferation of economic models and accounting tools of all kinds has added further confusion in assessing the impacts of the SDGs, thus compromising project success [31].

Despite this, there are initiatives by different countries, institutions, and non-governmental organizations toward developing strategies to align their projects with the SDGs. For example, the Government of Canada, through different universities such as Waterloo, Vancouver Island University, Laval, and other organizations, successfully funds projects based on the SDGs in local communities, provinces, and the private sector, among others [32]; the University of Newcastle (Australia) periodically issues reports on its activity in projects related to climate change, water purification, gender equality, non-poverty, etc. [33]; the Asia Society provides templates aimed at students where the schedule, program, objectives, expectations, tools, etc., are defined to incorporate the SDGs into projects [34]; Google Developer Student Clubs invites students to create projects that contribute in solving one or more of the SDGs, using Google technologies [35], etc.

1.4. Sustainability Ranking in Latin America and the Caribbean

To disseminate the repository, reports are periodically issued to show the world ranking compliance with the SDGs according to different countries.

In this regard, the average SDG index in Latin America and the Caribbean stood at a discreet 69.04/100 in 2022, with a general trend towards stagnation in the coming years [36].

Figure 1 shows the progress in meeting the SDGs for selected countries in Latin America and the Caribbean since 2015 and up to 2022.

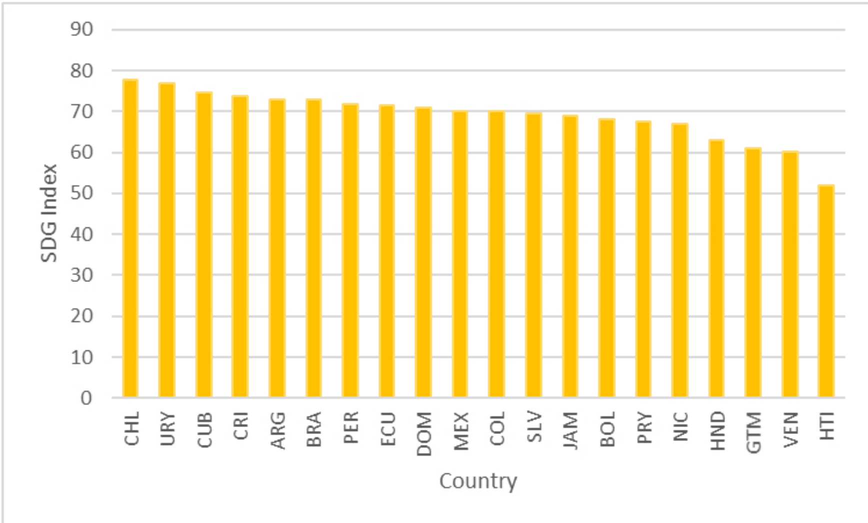

Figure 1. Global SDG Index Score (0–100) for some countries of Latin America and the Caribbean (2015–2022). Note. The difference at 100 is the distance needed in percentage to achieve the SDGs. Data are derived from indicators provided by official United Nations statistics and other non-traditional statistics, such as university centers and non-governmental organizations [36].

We can see that Chile, Uruguay, and Cuba are the three countries leading in the SDG compliance ranking, while Venezuela and, especially, Haiti occupy the last positions.

1.5. Project Selection and Classification

A total of 186 projects from Latin America (80.6%) and the Caribbean (19.4%) were selected and classified in this research article, covering a wide variety of aspects from service provision (30%), business creation (23%), building design, extensions, and refurbishments (19%), process redefinition (11%), product design and development (9%), and, lastly, people training (8%).

The selection included a grouping of the projects by dimension as a preliminary step toward a hierarchical ranking of sustainability, in reference to compliance with the SDGs (Table 4).

Table 4. Sub-sample list of 10 sustainability projects for local communities in Latin America and the Caribbean.

ID	Project	Dimensions *	SDGs **
1	Design and construction of infrastructure and public spaces on the right bank of the Chorobamba River in the city of Oxapampa, Perú	Infrastructure management Public and social sector management	Partnerships for the goals Clean water and sanitation Sustainable cities and communities Industry, innovation, and infrastructure Life on land
2	Wastewater treatment plant based on an oxidation lagoon for Los Portales housing, Piura, Perú	Infrastructure management Environment	Industry, innovation, and infrastructure Clean water and sanitation Life on land
3	Technical trade training center for low-income youth, Chile	Equality and inclusion Economic empowerment Education	Quality education Reduced inequalities Gender equality Decent work and economic growth No poverty
4	MSW sorting plant from the Municipality of Yerba Buena, Tucumán, Argentina	Economic empowerment Environment Infrastructure management	Sustainable cities and communities Responsible consumption and production
5	Housing project in El Cantón Pedernales–Manabí, Ecuador	Equality and inclusion Economic empowerment	Reduced inequalities Gender equality No poverty
6	Urban renewal plan for sidewalks surrounding the San Juan de Dios Hospital, San José, Costa Rica	Infrastructure management Public and social sector management	Partnerships for the goals Sustainable cities and communities Industry, innovation, and infrastructure Life on land
7	Environmental management plan for solid waste and organic waste generated by tourism activities around the Combeima River, Ibagué, Colombia	Environment Public and social sector management Economic empowerment	Partnerships for the goals Clean water and sanitation Sustainable cities and communities Life below water
8	Playa del Carmen Urban Planning Program, Quintana Roo, Mexico	Infrastructure management Public and social sector management	Partnerships for the goals Sustainable cities and communities Industry, innovation, and infrastructure Life on land
9	Accessibility program for people with disabilities in recreational spaces, San Pedro Sula, Honduras	Equality and inclusion Economic empowerment	Reduced inequalities Gender equality Decent work and economic growth
10	Training program for coffee producers in the municipality of Mesetas, Meta, Colombia	Equality and inclusion Economic empowerment Education	Quality education Reduced inequalities Gender equality Decent work and economic growth No poverty

Note. * Adapted from [37] and [38]. ** The most significant SDGs are shown.

As shown in Table 4, achieving sustainable development requires the participation of all actors in society, including local communities, which take a leading role in project management [39,40].

1.6. Artificial Intelligence and Sustainability

Artificial intelligence (AI) can be defined as software technology that encompasses one or more capabilities referring to perception, prediction, classification, decision making, diagnosis, and logical reasoning, among others [39].

This technology is fully compatible in complying with the SDGs, as stated annually in the summits organized by the International Telecommunication Union [41] in partnership with several entities and more than 35 UN agencies.

In successive meetings held periodically, the need for AI to accelerate compliance with the UN's SDGs is emphasized through the presentation of different projects aimed at this end [42].

Table 5 shows some of these activities. We can see that they refer to a wide variety of multidisciplinary sectors in the social, economic, and environmental fields.

Table 5. UN activities on artificial intelligence (AI) and relationship with the SDGs.

Partners	AI Activities	Related SDGs
Food and Agriculture Organization of the United Nations (FAO)	Fishing gear identification Animal disease identification from images Aquaculture mapping Detecting fall armyworm infestations	1–3 8,9 10–12
International Labor Organization (ILO)	From industrial robots to deep learning robots: the impact on jobs and employment The economics of artificial intelligence: Implications for the future of work Skills strategies for future labor markets	1–5 8–10 16,17
International Maritime Organization (IMO)	Maritime Autonomous Surface Ships (MASS) E-navigation Marine Environmental Protection and AI AI for Sustainable Maritime Transport (AI-SMART)	8,9, 11,13,14, 16,17
International Organization for Migration (IOM)	Humanitarian Data Science and Ethics Group IOM—Global Migration Data Analysis Centre (GMDAC) Applying techniques for internal quality control within the Displacement Tracking Matrix (DTM) Global Team	7,10 17
United Nations Program on HIV/AIDS	Health Innovation Exchange & TimBre Project: AIR-TB	3,4 9 17
United Nations Environment Program (UNEP)	Water-Related Ecosystems—SDG 6.6.1 UNEP Q & A Chatbot Funding Analysis and Prediction platform UNEP Robotic Process Automation	6 17
World Bank Group	Creating Global Public Goods Developing Knowledge and Policies Piloting Disruptive Technologies in World Bank operations Education-Use AI for Learning through Games Due Diligence—Predicting accounting red flags from external financial reports	1–3 9–11 13,16

Note. Adapted from [41].

On the other hand, a November 2018 McKinsey Global Institute study identified as many as 135 initiatives out of a possible 156 that fully or partially linked AI to one or more of the SDGs [38].

Figure 2 illustrates that most of these initiatives were related to Goals 3, "Good health and well-being", and 16, "Peace, justice, and strong institutions".

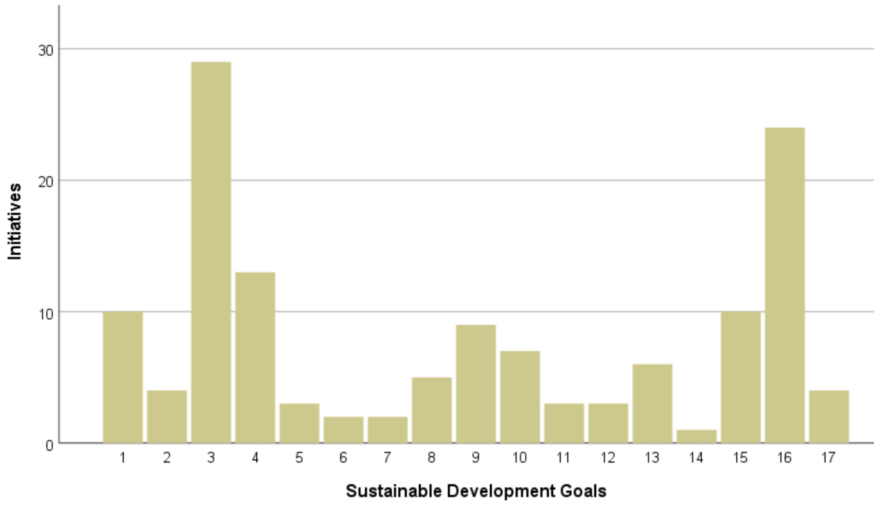

Figure 2. Number of project initiatives that fully or partially link AI to the SDGs. Note. Adapted from [38].

1.7. Machine Learning and Unbalanced Classes

Within the context of AI, machine learning constitutes a new paradigm integral to data mining techniques [43] that, among other functions, enables developing a predictive model with a large amount of data that can result in a numerical value (regression) or label a category of data (classification).

Depending on the type of output and processing approach, machine learning can be presented with examples of inputs and observed outputs (labels or targets), where the objective is that the model trains with this data set and learns to define a general rule that assigns the appropriate output label to a new value [44,45]. This type of classification, called supervised learning, is the one addressed in this research paper.

However, it is common for the metrics provided by the classifiers (their accuracy in particular) to be affected by classification problems of the variable to be predicted, where there is a class described as the majority that agglutinates a large proportion of the data, and other minority classes, poorly represented in terms of information. In this type of situation of unbalanced classes, it is common to resort to oversampling techniques, where the minority class is artificially increased (SMOTE).

1.8. Research Design

As we have seen, the few references that relate project management to the SDGs are aimed at very specific sectors and, at best, involve a few targets. Likewise, no literature on machine learning has been found either, which would help in reducing the existing gap between both concepts. The non-holistic conception prevailing in most of the projects also represents a problem for maintaining sustainability once the project has been implemented.

Having stated the problem of resistance to paradigm shifts in sustainable project management and leadership through AI, thus influencing the strategic objectives of the organization [46,47], the research question posed was as follows:

Is it possible to help bridge the gap between sustainability and project management by developing a holistic model based on machine learning, using the Sustainable Development Goals as input parameters to classify and forecast multi-sectorial projects according to their level of sustainability?

In this context, the guidelines followed in this research are shown in Table 6.

Table 6. Research design.

Unit of Analysis:	Sustainability of multi-sectorial projects in Latin America and the Caribbean
Dependent variable:	Level of implementation of Sustainable Development Goals Operational definition of the variable
Values of the dependent variable:	High, medium, low
Independent variables:	Sustainable Development Goals
How do you collect data on the presence or absence of the Sustainable Development Goals in your projects?	
Unit of observation:	Responses to Likert-scale questionnaires administered to expert panels

Note. Adapted from [48,49].

The research sub-questions were as follows:

- Why is it necessary to consider the Sustainable Development Goals to assess the sustainability of projects?
- Is it possible to develop the capabilities of a project manager within sustainable development terms?
- How can artificial intelligence break the current paradigm of sustainability through the Sustainable Development Goals?

The research was an objective type since, from the ontological point of view, it was assumed that the unit of observation—in this case, the answers to the Likert-scale questionnaires administered to expert panels—had its own identity constitution [49], while the authors of this research, as independent observers in reference to the nature of knowledge (epistemology), limited themselves in representing such reality with precision and accuracy [48].

2. Materials and Methods

The methodology followed in this research was descriptive and relational, quantitative, non-experimental, and transactional, because no hypotheses were proposed and no variable was manipulated, but it "[...] measured, evaluated, or collected data on various aspects, dimensions, or components of the phenomenon to investigate [in their natural work environment and in a single time]" [50,51].

As can be seen from the objective guiding this research work, the methodological scope comprised, broadly speaking, several distinct stages: first, a Likert-scale questionnaire based on the SDGs was prepared and provided to a group of experts for them to evaluate, on a scale of 1 to 5, the level of sustainability of 186 projects focused on local communities in various countries of Latin America and the Caribbean; second, the level of consensus among the group of experts and a global index of sustainability of the sample were determined using the Fuzzy Logic Designer tool of the Matlab R2021b mathematical software®; third, the classes of high, medium, and low were defined for the sustainability of the projects; fourth, the synthetic minority over-sampling technique (SMOTE) was included during the training phase of several supervised learning classifiers (Logistic Regression, K-Nearest Neighbors, Support Vector Machine, AdaBoost, Gaussian Process Classifier, and Random Forest), using the Scikit Learn library of Python 3.10. Lastly, the different resulting models were tested, and the one that offered the best accuracy for sustainability forecasting in future projects was chosen.

The panel of experts for evaluating the sustainability of the projects was composed of five groups of teachers and third-party professionals from the postgraduate course in design, management, and project management of the European University of the Atlantic (UNEATLANTICO), who previously established common guidelines toward achieving a good level of consensus.

2.1. Population and Sample

Initially, the study population consisted of a total of 210 international cooperation projects, targeting local communities in Latin American and Caribbean countries. To determine the necessary sample size, and given that the intention was to estimate percentage distributions of qualitative variables in the statistical calculations, Equation (1) for finite populations was used [52]:

$$n \geq \frac{N * Z^2_{1-\frac{\alpha}{2}} * (p * q)}{(N-1) * \varepsilon^2 + Z^2_{1-\frac{\alpha}{2}} * (p * q)} \tag{1}$$

where:

- n = required sample size;
- N = population size;
- $Z_{1-\alpha/2}$ = 1.96 (Z-statistic, calculated at 95% confidence level);
- p = q = 0.5 (typical values under worst-case conditions);
- Error (ε) = 0.05.

The sampling was convenience sampling—that is, non-probabilistic.

Substituting the values into the formula resulted in a required sample size for the study of $n \geq 136$.

2.2. Data Collection

As mentioned, the research instrument consisted of a Likert-scale questionnaire, which collected a total of 17 measurement criteria or items corresponding to each of the SDGs.

The scale categories were as follows: "1—Insignificant (I)"; "2—Not So Significant (NSS)"; "3—Significant (S)"; "4—Very Significant (VS)"; "5—The Most Significant (TMS)".

The information was collected between the dates of 1 January 2010 and 31 December 2019. A total of 210 projects were evaluated during this time, of which 24 were discarded due to deficiencies in the process.

2.3. Assessment of the SDG Indicators

The valuation method of the SDG indicators in the projects was inspired by the Sustainability Barometer, defined by the World Conservation Union [53].

The idea is that an objective, with a major environmental component—such as the purification of waste effluents—should not be achieved at any cost, but should maintain a balance with the other economic and social dimensions.

As illustrated in Figure 3, ecosystem well-being is located on the x-axis and socio-economic well-being on the y-axis. The intersection of the two provides a reading of the overall sustainability of the indicator, with the caveat that a low result on one axis cancels out the result on the other, with the more conservative approach prevailing in the final decision.

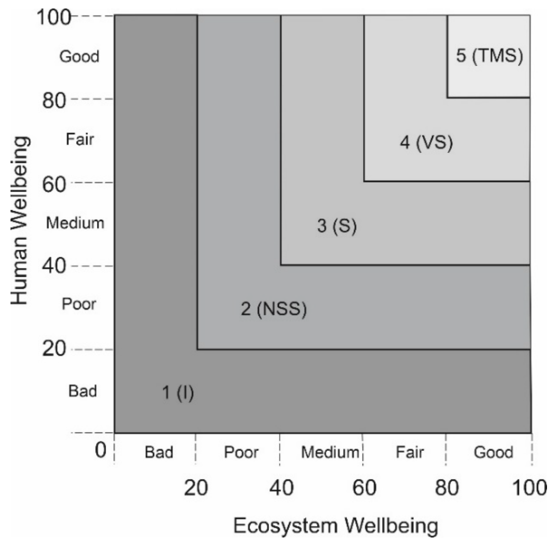

Figure 3. SDG indicator assessment method.

Figure 4 illustrates the main indicators of the SDGs, which were subsequently used by the experts in assessing the scale categories according to the Sustainability Barometer technique.

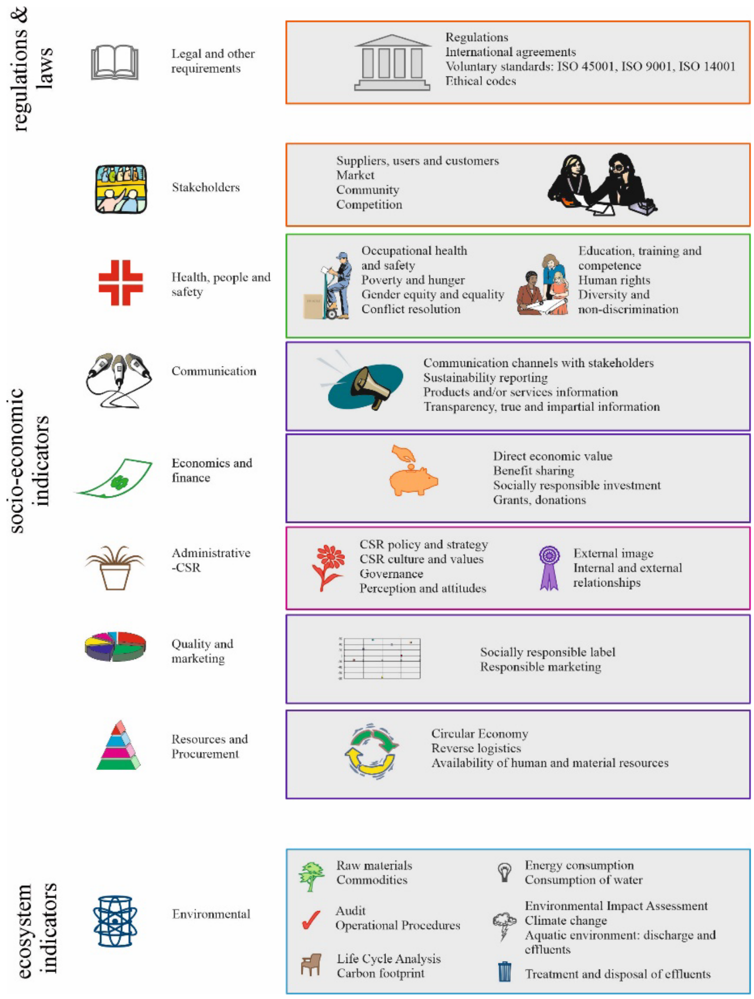

Figure 4. Main indicators of the SDGs used by experts. Note. Own elaboration.

2.4. Project Distributions among the Expert Panel

Project distributions among the expert groups was randomized, as illustrated in Table 7.

Table 7. Basic statistical parameters of project distributions among the groups of experts.

Expert Group	Number of Projects	Mean	Standard Deviation
1	40	4.0900	0.53340
2	41	4.1244	0.54067
3	40	4.0023	0.51783
4	33	4.0752	0.43769
5	32	3.9850	0.47944

Note. Own elaboration.

After verifying the validity and reliability of the proposed measuring instrument by means of Cronbach's Alpha statistic, an analysis of variance (ANOVA) was performed to determine whether there were significant differences between the groups' means or whether these were due exclusively to chance. To this end, data independence, normality, and homoscedasticity were tested. Both tests were performed using SPSS version 26 statistical software.

2.5. Data Preparation

Data preparation consisted of eliminating duplicate records or records with outliers, empty fields, etc.

2.6. Measurement of Expert Consensus

Consensus is defined as an opinion or position reached by a group of people as a general agreement [54].

As shown in Equation (2), consensus is a measure of attraction to a mean value:

$$\mathrm{Cns}(\mathrm{X}) = 1 + \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{p_i} \cdot \log_2\left(1 - \frac{|\mathrm{X_i} - \mu_\mathrm{x}|}{\mathrm{d_x}}\right) \quad (2)$$

where:

- X= list of categories ("1—Insignificant (I)"..."5—The Most Significant (TMS)");
- p_i = probability of each X;
- d_x = X_{max} -X_{min};
- X_i = particular element of X;
- μ_x = mean or expected value;

It is, therefore, a measure of dispersion for ordinal data in the interval [0, 1] and which, on a Likert scale with gradation between responses, can be transformed into the form of percentage agreement [55], as shown in Table 8.

Table 8. Expert consensus interpretation.

Interval	Consensus Classification
$Cns(X) \geq 90\%$	Very strong consensus
$80\% \leq Cns(X) < 90\%$	Strong consensus
$60\% \leq Cns(X) < 80\%$	Moderate consensus
$40\% \leq Cns(X) < 60\%$	Balance
$20\% \leq Cns(X) < 40\%$	Moderate dissent
$10\% \leq Cns(X) < 20\%$	Strong dissent
$Cns(X) < 10\%$	Very strong dissent

Note. Adapted from [56].

2.7. Categorization of Project Level of Sustainability

Each of the projects was then categorized into three classes (high, medium, low) according to their level of sustainability. To this end, a new variable, "Level of Sustainability", was created, containing the sum of the corresponding objective ratings for each of the projects ($\overline{x}$ = 69.75; s = 7.868).

Equation (3) below and Figure 5 provide the two cut-off points for defining the class categories:

$$\overline{x} \mp 0.75 \cdot s \cong Cut - off\ points \tag{3}$$

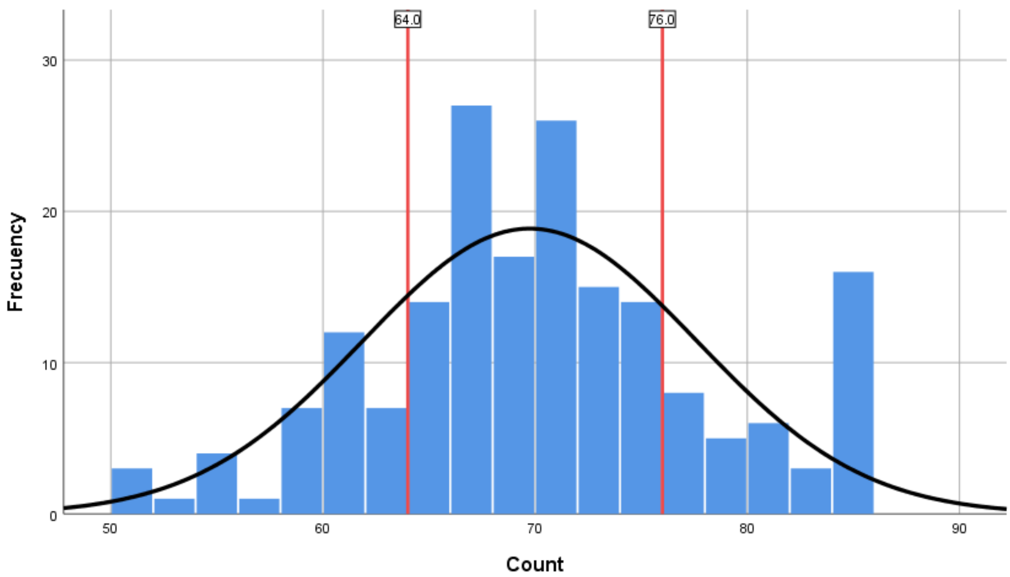

Figure 5. Frequency distribution of the "Level of Sustainability" variable and overprinted normal distribution curve. Note. The lower (64) and upper (76) cut-off values for the determination of class categories are represented.

2.8. Determination of a Global Sustainability Index for the Project Sample

The determination of the overall sustainability index of the sample was carried out using the fuzzy classifier incorporated in Matlab R2021b®. The input variables were, separately, the mean of the consensus corresponding to each of the dimensions, and the joint sustainability index obtained as an output variable in a gradation of five scales between the "very low" to "very high" linguistic variables.

The Mandani procedure [57] and triangular membership functions were used for their simplicity, functionality, and invariance for each score, which facilitated computational calculation at the intersections [58]. In this case, 3^3 fuzzy rules, obtained through expert judgment, were used.

2.9. Types of Classifiers

Table 9 shows the classifiers included in the Scikit Learn library of Python 3.10 and used in this research work.

Table 9. Classification algorithms and their characteristics.

Classification Algorithms	Features
Dummy Classifier (DMC)	It establishes an average reference metric (accuracy) and its standard deviation, by means of which to compare the rest of the classification algorithms.
Fuzzy Classifier	A different number of templates can belong partially to one class or to several classes. Class membership is measured by a number $\mu_A(x)$ in the interval [0,1], where $\mu_A(x) = \begin{cases} 0, & x \notin A \\ 1, & x \in A \\ ]0,1[& x \in A(p) \end{cases}$ where "A" is the class and "x" is the vector of characteristics or pattern.
Logistic Regression (LR)	It predicts the probability of an event or class occurring, conditional on a set of "n" independent variables. The model always returns the most probable class.
K-Nearest Neighbors (KNN)	During the training phase, it searches for the K-nearest neighbors of the point to be classified and subjects them to majority voting—for example, by weighting each neighbor's vote, according to the inverse square of their distances. An odd number of K will always be used to avoid possible ties.
Support Vector Machine (SVM)	It has also been reformulated for regression. The objective is to obtain the best "n-1" dimensional hyperplane to optimally separate one class from another, where "n" is the number of coordinate axes or independent variables. It is more efficient than KNN in terms of cost and accuracy.
AdaBoost (Adaptive Boosting)	It identifies those cases misclassified during training with several weak or base classifiers, giving them a higher weight or importance in successive cycles until the process stops for a certain minimum error value. Lastly, a final robust classifier is constructed as a weighted sum of the previous classifiers.
Gaussian Process Classifier	They are used for both regression and classification. They are based on the Gaussian probability distribution. As with SVMs, they require the specification of a covariance function (or kernel). The Gaussian process makes predictions with uncertainty and works well with a small data set, as is the case in this study.
Random Forest	It results from a combination of multiple decision trees created during the training phase. Each decision tree votes for one class, with the final result being the class with the highest number of votes in the entire forest.

Note. Own elaboration.

2.10. Data Resampling Techniques (SMOTE)

Data resampling techniques such as SMOTE achieve uniform distribution among unbalanced classes by altering the data distribution of the model. In this sense, the SMOTE algorithm, based on the K-Nearest-Neighbors classifier, served to create new instances within the minority classes [59,60].

2.11. Choice of the Best Classification Model

The stages implemented using the Scikit Learn library of Python 3.10 were the following:

- Data preparation and pre-processing;
- Data analysis and exploration;
- Assignment of the characteristic's matrix and the vector of classes or target;
- Codification of the vector of classes or target in dummy variables;

- Division of the data into training (80%) and testing (20%), with stratification of the output variable, to ensure homogeneity in the representativeness of the data in both groups.
- Training phase:
- Evaluation of the benchmark strategy with DummyClassifier.
- Elaboration of a pipeline containing the SMOTE oversampling technique, the scaling or normalization of the data, and the corresponding classifier.
- Use of the RepeatedStratifiedKFold cross-validation technique to minimize data overfitting.
- Use of the GridSearchCV technique to search for the best parameters.
- Testing phase:
- Model test with records not used during training (without SMOTE).
- Determination of metrics and choice of the model with the best accuracy.
- Printout of results.

2.12. Performance Evaluation Metrics

Table 10 shows the metrics used in this research paper.

Table 10. Performance evaluation metrics for a classification model.

Metric	Description
Overall accuracy rate $= \frac{tp+tn}{tp+fp+fn+tn}$	Overall hit percentage. Not a good indicator for unbalanced data.
Individual accuracy for class A $= \frac{tn}{tn+fn}$	Individual percentage hit rate per class. Can be used for unbalanced data.
Individual accuracy for class B $= \frac{fp}{fp+tp}$	
Sensitivity (recall) $= \frac{tp}{(tp+fn)}$	Proportion of positive cases correctly identified by the classifier. Determines when false negative costs are high.
Specificity $= \frac{tn}{(tn+fp)}$	Proportion of negative cases correctly identified by the classifier.
Precision $= \frac{tp}{(tp+fp)}$	Model quality level. Determines when false positive costs are high.
$f1 - score = 2 \cdot \frac{precision \cdot recall}{precision+recall}$	Is used to easily compare measures of precision and sensitivity in a single value. It is very useful for binary classification problems where the study is focused on the positive class, as is the case here.
Receiver Operating Characteristics (ROC) and Area Under Curve (AUC)	ROC is a probability curve that represents the fp rate on the abscissa axis and the tp rate on the ordinate axis for different thresholds. It indicates how much the model is able to distinguish between classes. The area under the AUC curve classifies the performance. The closer AUC is to unity, the better the model distinguishes between classes.

Note. tp: true positive; tn: true negative; fp: false positive; fn: false negative.

3. Results

3.1. Differences between Groups of Experts (ANOVA)

The analysis of variance to test whether there were differences between the means of the groups of experts resulted in compliance with the requirement of independence and Levene's test for homoscedasticity (constant variances), as each project was treated independently and provided a p-value of 0.6924 > 0.05, respectively. However, the Kolmogorov–Smirnov test resulted in a p-value < 0.0001, which, being less than 0.05, rejected the null hypothesis of normal data distribution, so that the data did not follow a normal distribution.

ANOVA is quite robust in the absence of normality, especially if the groups have a very similar size, as is the case; therefore, we can conclude that the means of the different groups being equal were accepted, and that the differences between groups were due exclusively to chance.

3.2. Validation and Reliability of the Measuring Instrument

Validation of the measurement instrument was based on the relevance, pertinence, and clarity of each of the 17 SDGs by a panel of experts [52].

Reliability was determined by means of Cronbach's Alpha statistic, and it included the set of objectives associated with sustainability.

The value of Cronbach's Alpha was 0.865, which is considered good data for the internal consistency of the instrument [61]. Among other aspects, this indicator ensures that the evaluation was not left to chance, so the study can proceed.

Table 11 shows the statistics associated with Cronbach's Alpha. The minimum value is 0.852, and the elimination of item 2 would improve the result (from 0.865 to 0.867). However, this small statistical improvement does not compensate for the loss of information due to the exclusion of the item, so it was decided to retain it.

Table 11. Statistics associated with Cronbach's Alpha.

Item	Scaling Average if the Element Has Been Suppressed	Scale Variance if the Element Has Been Suppressed	Total Correlation of Corrected Elements	Cronbach's Alpha if the Item Has Been Deleted
1	65.47	57.937	0.297	0.865
2	65.06	59.342	0.223	0.867
3	65.30	57.487	0.344	0.863
4	65.53	54.996	0.593	0.854
5	65.58	56.277	0.388	0.862
6	65.22	57.802	0.356	0.863
7	65.70	54.266	0.600	0.853
8	65.53	54.521	0.580	0.854
9	65.94	54.461	0.560	0.855
10	65.96	53.247	0.604	0.852
11	65.90	53.292	0.609	0.852
12	65.96	52.863	0.612	0.852
13	65.64	55.172	0.525	0.856
14	65.85	54.312	0.426	0.862
15	65.34	57.178	0.385	0.862
16	65.94	53.494	0.540	0.855
17	66.04	53.485	0.573	0.854

3.3. Consensus Measures

To determine consensus, the SDGs were grouped into three dimensions in this research, namely environmental, social, and economic, so that the same target could refer to multiple dimensions [62].

As shown in Table 12, a moderate consensus was obtained (see Table 8), with low levels of dispersion with respect to the weighted mean, demonstrating its reliability.

In this sense, the SDGs that obtained the highest consensus were Goal 2, "Zero hunger", with 79.87%, and Goal 6, "Clean water and sanitation", with 76.10%. Goal 14, "Life below water", obtained the lowest consensus, with 63.38%.

Table 12. Consensus measurement criteria.

Dimension	SDGs	Consensus Mean
Environmental	6, 7, 11–15	71.56
Social	1–5, 7, 8, 10–12, 16, 17	71.78
Economic	7–9, 11, 12	71.52
	Mean	71.66
	SD	3.70

3.4. Sustainability Level of the Project Sample

As a result of the classification, a typical situation of unbalanced data could be seen, where the majority class (medium) accounted for 60.2% of the projects, far behind the low and high classes, with 21.5% and 18.3%, respectively (Table 13).

Table 13. Percentage of sustainability level by grouping ranges.

Class	Grouping Range	Frequency	%
Low	Values ≤ 64	40	21.5
Medium	Values 64–76	112	60.2
High	Values ≥ 76	34	18.3

Note. Own elaboration.

3.5. Determination of the Global Sustainability Index for Projects

The overall sustainability index for the projects was 0.638, as illustrated in Figure 6.

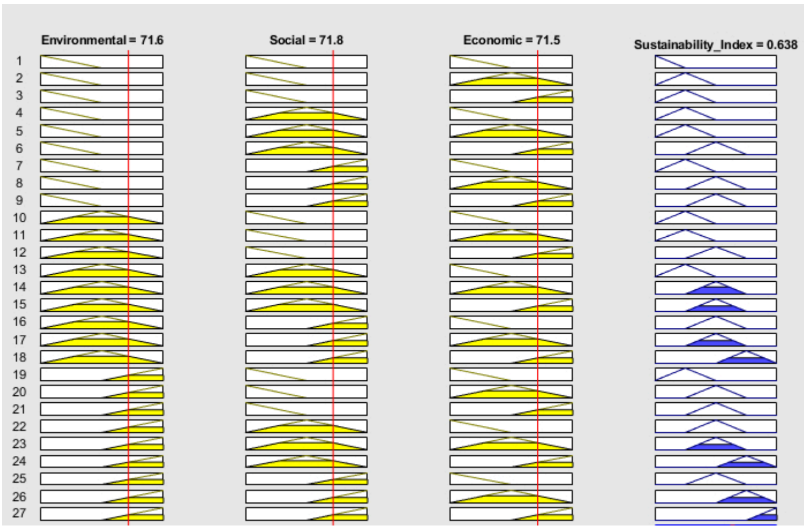

Figure 6. Overall sustainability index of the sample of projects based on the input consensus. Note. Own elaboration.

3.6. Accuracy Metric Threshold Determination

The DummyClassifier (DMC) classifier determined a threshold of 0.608 ± 0.01 for the accuracy metric, which also corresponds to the probability of finding a majority class 2 element within the training set (90 possible cases/148 total cases). This means that any model with an accuracy value below this threshold should be discarded.

3.7. Base Model Metrics

Figure 7 illustrates a comparative picture of the overall accuracy metric for the different classifiers implemented in the base model (unbalanced) during the training phase.

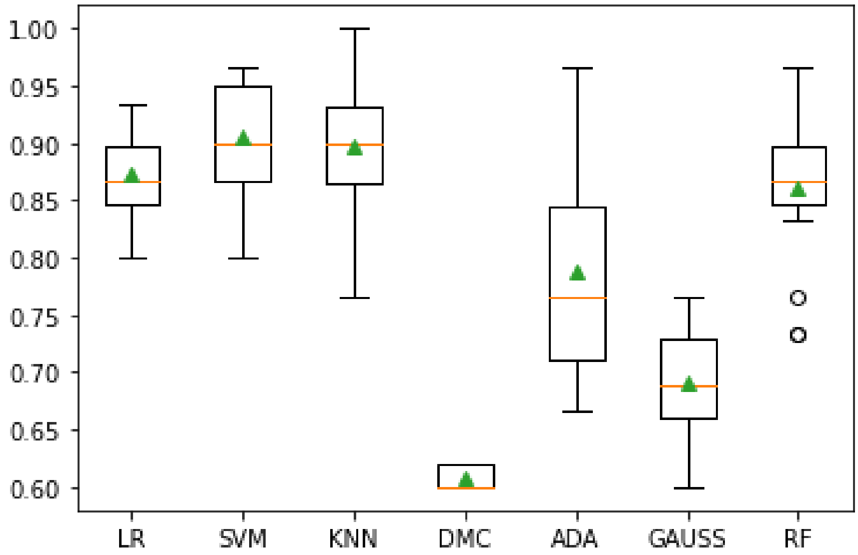

Figure 7. Comparison of the overall accuracy metric for different classifiers during the training phase of the unbalanced model. Note: The orange horizontal line refers to the median and the green triangle to the mean of the indicator.

The best classifiers are in the following order: SVM (0.906 ± 0.047); KNN(0.897 ± 0.057); LR(0.872 ± 0.045); RF(0.861 ± 0.069).

We can see that, in most of the classifiers, both the mean and the median are very close together, suggesting a certain symmetry and stability of the indicator distribution.

However, for unbalanced data, conclusions cannot be drawn from the overall accuracy metric alone [63,64], as it may not be considering the minority classes; therefore, in these circumstances, we must look for other types of metrics that can provide greater reliability in the interpretation of the indicators.

Table 14 shows the metrics obtained in the testing phase for the best classifiers. As can be seen, the order of importance of the classifiers is the same as that obtained during the training phase. It can be observed that the accuracy values achieved for each particular class are quite good.

In general, high values of precision and recall were obtained, indicating that the model generalizes said class perfectly. However, for the Random Forest model, maximum precision and low recall were obtained for the low class, suggesting that this model does not detect said class well, but, when it does, it is highly reliable.

Table 14. Set of metrics of the unbalanced models (testing phase).

Classifier	Class	tp	tn	fp	fn	Accuracy	Overall Accuracy	Precision	Recall	F1 Score	ROC/AUC
LR	High	5	29	2	2	0.89	0.84	0.71	0.71	0.71	0.98
	Low	6	30	0	2	0.95		1.00	0.75	0.86	1.00
	Medium	21	11	4	2	0.84		0.84	0.91	0.87	0.97
SVM	High	6	30	1	1	0.95	0.89	0.86	0.86	0.86	0.98
	Low	6	30	0	2	0.95		1.00	0.75	0.86	1.00
	Medium	22	12	3	1	0.89		0.88	0.96	0.92	0.97
RF	High	5	30	1	2	0.92	0.79	0.83	0.71	0.77	0.98
	Low	3	30	0	5	0.87		1.00	0.38	0.55	1.00
	Medium	22	8	7	1	0.79		0.76	0.96	0.85	0.94
KNN	High	6	29	2	1	0.92	0.84	0.75	0.86	0.80	0.99
	Low	5	30	0	3	0.92		1.00	0.62	0.77	0.88
	Medium	21	11	4	2	0.84		0.84	0.91	0.87	0.90

3.8. Balanced Model Metrics

Similarly, Figure 8 illustrates the comparison of the overall accuracy metric for the different classifiers implemented in the balanced model with SMOTE, during the training phase.

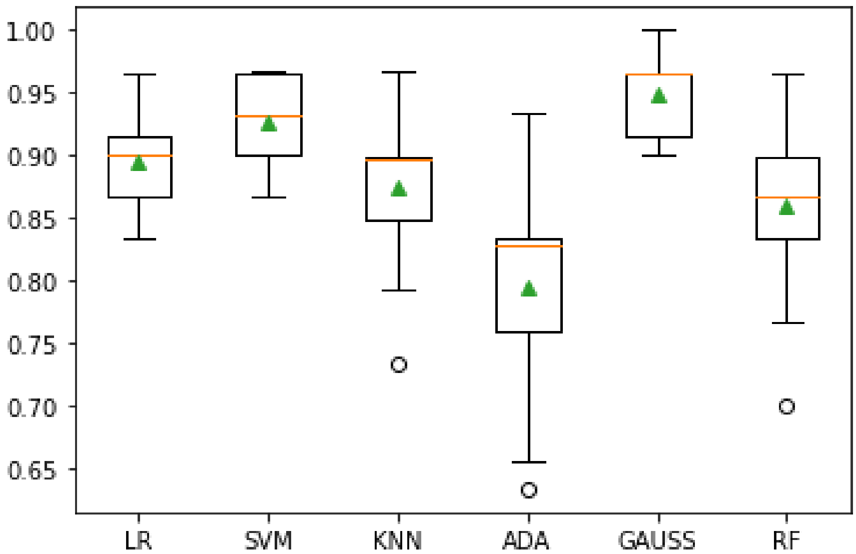

Figure 8. Comparison of the overall accuracy metric for different classifiers during the training phase of the balanced model. Note: The orange horizontal line refers to the median and the green triangle refers to the mean.

We can see how the improvement in this metric is significant when oversampling in three of the classifiers: GAUSS(0.948 ± 0.036); SVM (0.926 ± 0.033); LR(0.895 ± 0.041). Meanwhile, for KNN(0.874 ± 0.057) and RF(0.859 ± 0.065), it worsens slightly.

Table 15 shows the metrics obtained during the testing phase for the best classifiers with oversampling. As can be seen, the best classifier is SVM, with overall accuracy of 0.92, similar to that obtained during the training phase, which, as in the case of the LR and KNN classifiers, suggests the good generalization of the model. In the case of the GAUSS classifier, a value of 0.87 << 0.94 is obtained, indicating probable overfitting.

Table 15. Set of metrics of the balanced models (testing phase).

Classifier	Class	tp	tn	fp	fn	Accuracy	Overall Accuracy	Precision	Recall	F1 Score	ROC/AUC
LR	High	7	29	2	0	0.95	0.89	0.78	1.00	0.88	0.98
	Low	6	30	0	2	0.95		1.00	0.75	0.86	1.00
	Medium	21	13	2	2	0.89		0.91	0.91	0.91	0.97
SVM	High	7	29	2	0	0.95	0.92	0.78	1.00	0.88	0.99
	Low	7	30	0	1	0.97		1.00	0.88	0.93	1.00
	Medium	21	14	1	2	0.92		0.95	0.91	0.93	0.98
GAUSS	High	5	30	1	2	0.92	0.87	0.83	0.71	0.77	0.98
	Low	6	30	0	2	0.95		1.00	0.75	0.86	1.00
	Medium	22	11	4	1	0.87		0.85	0.96	0.90	0.97
KNN	High	7	29	2	0	0.95	0.87	0.78	1.00	0.88	0.98
	Low	6	29	1	2	0.92		0.86	0.75	0.80	0.99
	Medium	20	13	2	3	0.87		0.91	0.87	0.89	0.95

4. Discussion

To help to bridge the gap between sustainability and project management, a methodology based on the SDGs was developed to assess sustainability in a sample of multi-sectoral projects in the Latin American and Caribbean region. This is important because, while there are numerous models that relate project management to sustainability in specific sectors, there are few that involve the SDGs in the creation of shared value. In this sense, [27] highlight the role of project managers in taking a leading role in the creation of a conceptual framework to measure the impacts of the SDGs on projects through the lens of TBL. However, the acquisition of competencies and tools is not always the most appropriate, meaning that solutions to problems are sought based on the immediacy and benefit of the results, instead of developing strategies that involve the entire project development process. Along the same lines, [65] and [66] consider that the SDGs should be deemed as key inputs to the business strategy and not as an additional external cost to the company, integrating them into the project life cycle. On the opposite side, other authors question the ability of the SDGs to determine project success. For example, [67] base their analysis on urban indicators and justify their argument by the variability and complexity of their definition; the political nature of the data; the scarce availability of standardized, open, and comparable data; the lack of solid institutions for data collection and monitoring; and, lastly, the difficulty of their application toward different local communities. Along the same lines, [68] provide a more environmentalist view and justify their argument in the proliferation of undefined and unmeasurable ideals, with the approach ambiguity of the SDGs 14 and 15 as an example.

Artificial intelligence was used in this research article to diagnose, classify, and predict the sustainability of a sample of projects aimed at local communities in Latin America and the Caribbean, using the fulfillment of the SDGs as a reference.

In the literature, we found experiences of classification and the classification of projects in relation to their degree of complexity [69], strategies [70], construction and sustainable infrastructure [71], and leadership styles [72], among others; however, we found no precedents for the classification of projects based on machine learning that took into account the level of compliance with the SDGs in local communities in Latin America and the Caribbean.

In reference to the diagnosis of the sustainability scope, Latin America and the Caribbean recorded a discreet value of 69.04/100 until the year 2022—that is, an advance of only 1.19% compared to 2015 [36] and three points above the value of the world average index of 66 for the same year.

This figure, compounded by the pandemic caused by SARS-CoV-2, means that progress is not being made at an adequate pace to meet the 2030 Agenda [73]. In this context, the worst-performing SDGs in the region were 10—Reduced inequalities; 9—Industry, innovation, and infrastructure; and 16—Peace, justice, and strong institutions [36].

Indeed, aspects such as the quality and equity of Internet access, economic slowdown, inequality, wage and gender gaps, and the fight against corruption, among others, are the major challenges currently facing the region [22,74]. In this context, we believe that project management and leadership is an excellent opportunity toward addressing the challenges posed by these objectives and, thus, implementing good practices in local communities in Latin America and the Caribbean.

During the course of the research, we saw that AI technology is closely linked to the fulfilment of the SDGs. In this regard, AI's relevance to the SDGs was noted in numerous summits organized by the International Telecommunication Union (ITU) under the auspices of the United Nations, from which a large number of initiatives and projects have emerged [42]. Many of them are related to goals 3, Good health and well-being, and 16, Peace, justice, and strong institutions [38]. This means that there is a special consideration in AI for issues that affect health and governance—for example, in Latin America and the Caribbean, in relation to HIV infections, quality of healthcare services, teenage pregnancies, communicable and emerging diseases such as cholera, dengue, zika virus, COVID-19, among others. These results are corroborated by authors such as Vinuesa et al. [75], who believe that AI can facilitate 80% of the fulfillment of the SDGs; however, it can also constitute a constraint due to the price of the technology. In this context, we consider that AI is necessary for the fulfilment of the SDGSs, but always adopting compromising solutions between the cost of the technology and the benefits derived from its implementation, which is, in turn, the foundation of the concept of sustainable development [76,77].

When determining the overall sustainability level of the project samples, very similar consensus values were obtained between the groups of experts and dimensions: Environment (71.6), Social (71.8), and Economic (71.5). There were no significant differences between the expert panels, by which the variations between group averages were attributable to chance. These consensuses averaged an overall mean rating of 0.638 on a fuzzy set system corresponding to a medium level of sustainability. These data are a true reflection of the compliance of the SDGs in Latin America and the Caribbean to date, since, as we have seen, the SDG Index is also within an equivalent position in the region [36], which confirms the model's robustness. This procedure is corroborated by Encarnacion [55], who, in his research, uses, as parameters of the input variable, the consensuses calculated as a measure of dispersion for ordinal category data. In this sense, the consensuses presented a low level of dispersion in general, which ratified the consistency of the weighted mean.

Prior to the model training phase, the sample of projects was categorized according to their level of sustainability. This classification resulted in the following percentages: high (18.3%), medium (60.2%), and low (21.5%). These provided the desired values or targets for supervised learning. We can see that most of the sample presented a medium level of sustainability, which is consistent with the result obtained through the fuzzy set system.

In reference to finding the best model for predicting sustainability in projects aimed at local communities in Latin America and the Caribbean, the Gaussian Process Classifier was found to have a very good fit during the training phase (0.948); however, accuracy dropped significantly during the training phase (0.87), indicating the possibility of overfitting. This is because the use of resampling techniques such as SMOTE can introduce examples from the minority classes into the majority class and cause, in practice, problems of overfitting or underfitting, which could invalidate the model [78].

Lastly, the SVM + SMOTE classifier was the one that obtained the best level of accuracy, both globally (0.92) and individually (H: 0.95; M: 0.97; L: 0.92), for each of the classes, superior to the rest of the classifiers during the testing phase. These metrics were quite similar to those obtained during the training phase, which indicates the good generalization of the model, i.e., no overfitting. These results are consistent with those found by Demidova and Klyueva [79], where it is concluded that the SMOTE algorithm significantly improves the metrics of the SVM classifier, even with very unbalanced data.

5. Conclusions

This research article has tried to develop a methodology based on guaranteeing project sustainability from a holistic perspective, abandoning the CSR approach, and adopting sustainable criteria beyond the triangular relationship (time, cost, and scope) of the traditional project manager's vision.

In this sense, the analysis of the literature review on sustainability and project management revealed that:

- There was a gap between sustainability and its application to project management;
- the integration of sustainability should take place throughout the entire project life cycle and not only focus on the outcome; and,
- the sustainability assessment of the project should consider a set of targets and indicators based on TBL.

Although the integration of sustainability into the project life cycle process is beyond the scope of this research, it is appropriate to mention the need for establishing a new paradigm to help to bridge the gap between the perception of sustainability—and the SDGs—and its application to project management.

In this way, an affirmative answer to the research question was provided by developing a machine learning model to classify and evaluate project sustainability. In this regard, the result showed that the classifier (SVM + SMOTE) was the best option, with overall accuracy of 0.92, suggesting the good generalization of the model.

Therefore, artificial intelligence is an innovative tool for bringing the SDGs closer to managing projects aimed at local communities, particularly in Latin America and the Caribbean. The model can be used, in this case, to identify negative externalities and inefficiencies in projects and adopt the corresponding internalization measures—for example in the areas of greatest concern within the region, such as social inequalities, pollution, and corruption or discriminatory laws.

On the other hand, although this is a contentious aspect, the use of the SDGs as independent variables of the model simplifies and organizes the targets and indicators, providing a framework for the feasibility of measuring project sustainability. With this relating to another of the research sub-questions, it was shown that, given the existing confusion between the terms and definitions of sustainability and its application in project management, training the project manager in general, and particularly in the field of the SDGs, is essential in extending the benefits of the results beyond the early stages of project implementation.

Lastly, the methodology followed in this research and the approach to measuring the SDGs can link the results obtained in the projects to improve the national and global indices of the region.

6. Recommendations

In the future, this research can be improved by expanding the sample of projects and their characteristics to other communities different from Latin America and the Caribbean. A neural network model with SMOTE could also be included, and even other techniques that do not alter the data distribution, such as adjusting the optimal prediction probability threshold or the hyperparameter penalty, which could be tested.

7. Limitations

The main limitations of the methodology described in this research article are based on the difficulty in establishing a well-defined conceptual framework, given the differences between the global definitions of the SDGs' objectives and their application at the project management level [65]. This means that, sometimes, for a specific sector, the model does not cover all the necessary indicators.

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