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A Data-Driven Framework for Assessing Sustainability-Oriented Research Models in Higher Education Institutions

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Abstract

Sustainability has become a strategic priority for Higher Education Institutions (HEIs), particularly in the context of the Sustainable Development Goals, where university research plays a key role in addressing environmental, social, economic, and institutional challenges. However, the evaluation of sustainability-oriented research models remains limited by fragmented indicators, descriptive approaches, and the absence of robust, data-driven assessment frameworks. This study proposes a comprehensive framework for assessing the sustainability orientation of university research models, integrating validated measurement instruments with advanced analytical and predictive techniques to support evidence-based decision-making in higher education governance. The framework is based on a multidimensional instrument comprising 26 indicators across environmental, social, economic, and institutional dimensions, developed through expert judgment using the Delphi method and statistically validated by Confirmatory Factor Analysis (CFA). The instrument was applied to 260 researchers from four public HEIs located in the Colombia–Ecuador border region, and perceived performance was contrasted with actual institutional indicators, revealing significant non-linear discrepancies. To address this complexity, an artificial neural network model was developed to estimate real sustainability performance based on survey data, achieving a predictive accuracy of 90.92%. Beyond institutional diagnosis, the proposed framework functions as a decision-support tool that enables HEIs to identify critical gaps, prioritize interventions, and guide continuous improvement strategies in research management. Due to its methodological rigor, scalability, and transferability, the framework can be adapted to different higher education contexts, contributing to the advancement of sustainability assessment methods and governance practices in universities.

Keywords: sustainability assessment; higher education institutions; university research models; data-driven decision-making; confirmatory factor analysis; neural networks; sustainability governance

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1. Introduction

Higher Education Institutions (HEIs) play a central role in advancing sustainable development through knowledge generation, innovation, and the transfer of research outcomes to society. In the context of the Sustainable Development Goals (SDGs), universities are increasingly expected to align their research systems with environmental protection, social equity, economic resilience, and institutional responsibility [1,2,6]. As a result, sustainability has become a strategic dimension of university governance, requiring systematic evaluation mechanisms that allow institutions to monitor, assess, and improve the sustainability orientation of their research models [5,9].

Despite the growing consensus on the importance of sustainability in higher education, significant challenges persist in the evaluation of university research systems. Existing approaches frequently rely on isolated indicators, descriptive reports, or administrative metrics that fail to capture the multidimensional and dynamic nature of sustainability [9,10]. Moreover, many proposed frameworks remain at a conceptual level or lack rigorous statistical validation, limiting their usefulness for evidence-based decision-making in institutional management [7,11]. These limitations are particularly evident in public HEIs operating in complex territorial contexts, where sustainability challenges are intensified by social, economic, and environmental constraints [6].

Recent literature emphasizes the need for integrated and data-driven assessment frameworks capable of evaluating sustainability performance across multiple dimensions within higher education systems [8,9,12]. Such frameworks should combine robust measurement instruments with advanced analytical methods to reduce subjectivity, capture non-linear relationships, and support continuous improvement processes [10]. In this context, quantitative approaches based on multivariate statistical techniques—such as Confirmatory Factor Analysis (CFA)—have proven effective for validating sustainability-related constructs and ensuring measurement reliability in higher education research [14,16].

In parallel, the growing availability of institutional data has fostered the adoption of artificial intelligence and machine learning techniques in sustainability assessment and university governance [22,23]. Artificial neural networks, in particular, have demonstrated strong potential for modeling complex, non-linear relationships between perceptions, behaviors, and institutional performance, offering predictive capabilities that traditional linear models cannot provide [24,25]. When integrated with validated measurement instruments, these techniques enable the development of decision-support systems that translate empirical data into actionable insights for sustainability-oriented management.

From a sustainability assessment perspective, university research models constitute a critical unit of analysis within HEIs. Research policies, funding structures, academic practices, and engagement with society directly influence the extent to which universities contribute to sustainable development [3,4]. However, systematic tools specifically designed to evaluate sustainability-oriented research models—integrating environmental, social, economic, and institutional dimensions—remain scarce, particularly in the context of Latin American public universities [9,11]. The absence of validated instruments and predictive models limits the ability of HEIs to identify performance gaps, prioritize interventions, and design evidence-based governance strategies.

This study addresses these gaps by proposing a data-driven framework for evaluating sustainability-oriented research models in Higher Education Institutions. The framework integrates a multidimensional instrument developed through expert judgment and validated using Confirmatory Factor Analysis, with an artificial neural network model designed to predict real sustainability performance based on researchers' perceptions. The empirical application focuses on four public HEIs located in the Colombia–Ecuador border region, a territory characterized by pronounced sustainability challenges and strong demands for socially relevant research [2,6].

The specific objectives of this research are: (i) to construct and statistically validate an instrument for assessing the sustainability orientation of university research models; (ii) to analyze discrepancies between perceived and actual institutional performance using multivariate techniques; and (iii) to develop an intelligent predictive model that supports evidence-based decision-making in university research governance. By combining explanatory and predictive approaches, the proposed framework goes beyond descriptive evaluation and functions as a practical decision-support tool for sustainability-oriented management.

The main contribution of this study lies in its methodological rigor, analytical depth, and practical applicability. The validated instrument and the neural network-based model provide transferable and scalable tools that can be adapted to different institutional and territorial contexts. In line with the scope of *Sustainability*, this research contributes to the advancement of sustainability assessment methodologies in higher education and supports the development of more resilient, accountable, and sustainability-oriented university research systems [9,10].

1.1. Related Works

Research carried out by Higher Education Institutions (HEIs) plays a leading and indispensable role in the sustainable development of societies [1]. As noted by [2,3], university research is key to generating the knowledge, innovations, and solutions required to promote environmentally sustainable, socially inclusive, and economically vibrant progress. Therefore, it is essential for HEIs to have relevant research models that effectively guide their research capacities to strategically address the needs and priorities of their context [4].

In the current context, relevance in university research models implies adopting a sustainability-oriented approach in a transversal and holistic manner. As stated by [5,6], sustainability must be embedded in all areas of HEIs, including their research systems. This requires research models to incorporate objectives, policies, procedures, and practices that explicitly promote the generation of knowledge for sustainable development in its multiple dimensions [7].

The core components of university research models must be tangibly linked to concrete sustainability indicators, considering their environmental, social, economic, and institutional dimensions in an integrated manner [8]. Aspects such as funding, human resource allocation, infrastructure, scientific production processes, and dissemination and social engagement activities, among others, must be intentionally aligned with clearly specified sustainability goals and indicators [9]. Only in this way can university research optimally contribute to addressing pressing challenges such as climate change, social inequalities, poverty, and biodiversity loss.

For this reason, it is valuable and strategic to have comprehensive tools that allow for the evaluation of the actual level of compliance of university research models with concrete sustainability indicators across their environmental, social, economic, and institutional dimensions. Such instruments make it possible to conduct a detailed and evidence-based diagnosis of the strengths and weaknesses of existing models [10], and subsequently to propose well-founded and specific improvements that optimally adjust these models, so that university research is oriented toward sustainability in the most effective way [11]. In addition, these tools enable the monitoring and comparison of progress among different HEIs over time [12]. Undoubtedly, the availability of robust instruments to evaluate and strengthen the incorporation of sustainability into university research systems constitutes a relevant contribution, which could be replicated and adapted to optimize research models in diverse contexts.

2. Materials and Methods

The research was conducted within the geographical framework of the border area between Ecuador and Colombia, specifically in four public Higher Education Institutions (HEIs) located in this territory. On the Ecuadorian side, the Universidad Técnica del Norte and the Universidad Politécnica Estatal del Carchi were included, while on the Colombian side, the Universidad de Nariño and the Escuela Superior de Administración Pública, Pasto campus, participated.

The development of the stages of this research was based on the Delphi methodology [13], whose phases were carried out with meticulousness and precision. The first phase of the process consisted of the identification of experts in the area of sustainability, for which a group of outstanding specialists was selected; for the initial round, the experts belonged to the research group "Sociedad Sustentable" of the Universidad Politécnica Estatal del Carchi. In a subsequent phase, for the concluding round, researchers from various HEIs were identified, both at the national and international levels.

Subsequently, a call phase was carried out, during which the identified experts were contacted and invited to participate in the Delphi process. This invitation included a detailed explanation of the purpose of the research, the methodology to be used, and the estimated duration of the process, thus seeking to provide a clear and comprehensive overview of the expectations and responsibilities involved.

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Finally, in the question preparation phase, an initial questionnaire composed of four open-ended questions detailed in Table 1 was designed. These were aimed at identifying, under expert judgment, the indicators relevant to each dimension of sustainability. It is imperative to highlight that the structuring of these questions was meticulously developed, seeking to create a space for responses that would provide valuable insights oriented toward the generation of strong and applicable knowledge within the analyzed geographical and institutional context.

Table 1. Questions formulated to identify indicators relevant to each dimension of sustainability.

Description	
Code	Question
$\boldsymbol{p}1$	What should be the indicators that should form part of the social dimension for a research model of an HEI located in the Colombia–Ecuador border area?
$\boldsymbol{p}2$	What percentage of the Research Department's budget for the development of sustainability-oriented research activities comes from external funding?
$\boldsymbol{p}3$	What percentage of the Research Department's budget is used to grant incentives for research activities focused on sustainability?
$\boldsymbol{p}4$	What is the number of sustainability-related research activities carried out ad honorem?

It is imperative to emphasize that the survey was conducted in an anonymous format, ensuring through the configuration of the platform used for data collection that the responses provided by the experts remained anonymous throughout the entire process.

In the first instance, the initial questionnaire was sent to the selected experts for the corresponding round, establishing a defined period for its completion. Subsequently, the responses were collected and analyzed, carefully examining the preliminary opinions and assessments provided. Thereafter, the responses from the initial round were summarized, and the experts were provided with an anonymous compendium containing the responses and comments of the other participants.

Based on these results, the initial matrix was constructed, integrating the sustainability dimensions along with their respective indicators. During the application phase of this matrix, the responses were evaluated, consensually discussed, and adapted. The responses generated by the experts in the initial round were then sent to researchers from external HEIs in the form of an instrument consisting of 26 ordinal questions on a Likert scale, with the objective of incorporating their perceptions and contributions. Finally, the results were summarized and documented in a matrix that incorporated the recommendations and contributions of experts from external HEIs. The developed instrument is presented in Table 2.

Table 2. Preguntas formuladas para el instrumento aplicado a los investigadores de las IES participantes.

Economic dimension	
Code	Question
$\boldsymbol{p}4$	There is a considerable percentage of the Research Department's budget for the development of sustainability-oriented research activities coming from external funding.
$\boldsymbol{p}5$	The percentage of the Research Department's budget used to grant incentives for research activities focused on sustainability is adequate.
$\boldsymbol{p}6$	The IES develops a considerable number of *ad honorem* sustainability-related research activities per year.
$\boldsymbol{p}7$	There is an adequate percentage of research projects involved in the optimization of economic resources through sustainable alternatives.
$\boldsymbol{p}8$	There is an adequate percentage of research projects based on local and regional development with a sustainability focus.
Social dimension	

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$\boldsymbol{p}9$	There is an adequate number of departments and/or centers that carry out research activities providing services to society.
$\boldsymbol{p}10$	There is a considerable number of sustainability reports and/or documents derived from research activities that are published by the IES and linked to society per year.
$\boldsymbol{p}11$	There is equity in gender participation in research activities.
$\boldsymbol{p}12$	There is an adequate percentage of research projects related to renewable energy, ecological economics, urban planning, or other aspects of an environmental nature.
Environmental dimension	
$\boldsymbol{p}13$	There is an acceptable number of departments, units, or environmental management centers that conduct research.
$\boldsymbol{p}14$	The IES organizes a significant number of scientific events oriented toward the environmental component per year.
$\boldsymbol{p}15$	There is a significant percentage of research groups whose practice is focused on the environmental dimension.
$\boldsymbol{p}16$	There is a significant percentage of research seedbeds that focus their work on the environmental dimension.
$\boldsymbol{p}17$	The IES has a significant number of annual participations in external scientific events oriented toward the environmental component.
$\boldsymbol{p}18$	The institutional mission and vision are linked to the principles of sustainability.
Institutional dimension	
$\boldsymbol{p}19$	A considerable percentage of the IES's research faculty has training in sustainability.
$\boldsymbol{p}20$	The percentage of students who graduate with research topics in sustainability in the degree or program in which you work is considerable.
$\boldsymbol{p}21$	The institutional educational model includes curricular spaces oriented toward formative research under a sustainability approach.
$\boldsymbol{p}22$	There is a considerable number of research publications per year focused on topics related to sustainability.
$\boldsymbol{p}23$	There is an appropriate number of clubs focused on research and sustainability activities.
$\boldsymbol{p}24$	There is an appropriate number of research groups focused on research and sustainability activities.
$\boldsymbol{p}25$	There is an appropriate number of research seedbeds focused on research and sustainability activities.
$\boldsymbol{p}26$	The percentage of postgraduate programs that have an approach exclusively based on sustainability is adequate.

After analyzing the indicators consolidated in the final matrix, their theoretical grounding within the research framework was strengthened, and two instruments derived from this matrix were structured. The first instrument was focused on obtaining specific and direct information from the representatives of the Research Departments of the evaluated HEIs, while the second instrument was aimed at exploring the degree of perceived compliance with each of the indicators by the surveyed researcher faculty members.

Data treatment. The compilation of a database for any scientific study has the potential to contain missing and outlier data; therefore, it is noted that any statistical analysis must begin with the implementation of a meticulous data analysis protocol. Among the prevalent techniques for data handling in multivariate samples is the use of Mahalanobis distances. This technique facilitates the measurement of the number of standard deviations by which an observation is located with respect to the mean of a distribution. Since outliers do not behave in the same way as regular observations, this measure can be used for the detection of anomalous observations. From a geometric perspective, while Euclidean distance is the shortest distance between two points, it does not incorporate in its calculation the existing relationship among variables that are highly correlated. In contrast, Mahalanobis distance does take into account the correlation between variable [14,15]. This scale-invariant metric considers the measurement of the distance between a point $\boldsymbol{x} \in \mathbb{R}^p$ rawn from a p-

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variate probability distribution $f_X(.)$, $\boldsymbol{p}$- varied and the mean $\boldsymbol{\mu} = \boldsymbol{E}(\boldsymbol{X})$ of the distribution. Under the assumption that the distribution $f_X(.)$ has finite second-order moments, the covariance matrix can be determined as $\sum = \boldsymbol{E}(\boldsymbol{X} - \mu)$. Thus, the Mahalanobis distances are defined as:

$$\boldsymbol{D}(\boldsymbol{X}, \mu) = \sqrt{(\boldsymbol{X} - \mu)^T \Sigma^{-1} (\boldsymbol{X} - \mu)}. \quad (1)$$

Confirmatory factor analysis. Once the processed data were available, confirmatory factor analysis was applied to verify the validity and reliability of the instrument. Confirmatory factor analysis (CFA) is a technique used to test the variables that make up a construct, considering the dependence of each variable on the factor from which it originates. CFA stands out as an advantageous technique in the analysis of ordinal variables, through which it is possible to discern the extent to which the p × 1 response vector constructed from observable random variables is capable of explaining one or more unobserved variables, known as factors $\boldsymbol{\eta}$. hrough this procedure, each proposed variable contributes to explaining the behavior of the unobserved latent variable that is evaluated and estimated. In this model, a vector of observed responses $\boldsymbol{Y}_i$ is considered to explain the unobserved latent variable $\boldsymbol{\xi}$ using the model.

$$\boldsymbol{Y} = \boldsymbol{\Lambda}\, \boldsymbol{\xi} + \boldsymbol{\epsilon}, \quad (2)$$

Where $\boldsymbol{Y}$ represents the $\boldsymbol{p} \times 1$ vector of observed random variables, $\boldsymbol{\xi}$ corresponds to unobserved variables, and $\boldsymbol{\Lambda}$ denotes a $\boldsymbol{p} \times \boldsymbol{k}$ matrix where k represents the number of unobserved latent variables, where $\boldsymbol{k}$ represents the number of unobserved latent variables. Since $\boldsymbol{Y}$ is composed of a set of unobserved latent variables $\boldsymbol{\xi}$, the model includes the error term $\boldsymbol{\epsilon}$. This model can be solved using maximum likelihood (ML) estimation, generated through the iterative minimization of the function:

$$F_{ML} = \boldsymbol{ln}|\boldsymbol{\Lambda\Omega\Lambda}' + \boldsymbol{I} - diag(\boldsymbol{\Lambda\Omega\Lambda}')| + \boldsymbol{tr}\big(R(\boldsymbol{\Lambda\Omega\Lambda}' + \boldsymbol{I} - -diag(\boldsymbol{\Lambda\Omega\Lambda}')^{-1})\big) \quad (3)$$
$$- ln(R) - \boldsymbol{p},$$

where $\boldsymbol{\Lambda\Omega\Lambda}'$ represents the variance–covariance matrix derived from the proposed factor analysis model, and $\boldsymbol{R}$ corresponds to the observed variance–covariance matrix. More specifically, in Confirmatory Factor Analysis (CFA), the model parameters can be estimated by minimizing the distance between the variance–covariance matrix implied by the model and the observed matrix [16–21].

Análisis de componentes principales. Principal Component Analysis (PCA) was employed as a dimensionality reduction technique, with the underlying objective of transforming a set of correlated variables into a set of uncorrelated variables. PCA has been commonly used as an exploratory data analysis technique, through which the existing relationships among a set of variables are examined, thus positioning it as a suitable technique for dimensionality reduction. This method, by seeking to transform an original number of possibly correlated variables into a smaller number of uncorrelated variables known as principal components, facilitates the interpretation of complex datasets by preserving, as much as possible, the total variance of the data. The first principal component is defined in such a way that it retains the maximum possible variance of the original data, and each subsequent component, in turn, captures the maximum remaining variance under the constraint of being orthogonal to the previous components. [22]. In addition, as described in [23,24], el PCA can be used to determine the number of hidden layers to be implemented in a neural network. For a dataset $x^{(1)}, x^{(2)}, \cdots, x^{(m)}$ with n-dimensional observations, the aim is to project the dataset onto k-dimensional observations (where $k < n$). o this end, the process begins with data standardization:

$$x_j^i = \frac{x_j^i - \bar{x}_j}{\sigma_j}, \quad (2)$$

Then, the covariance matrix is calculated as follows:

$$\Sigma = \frac{1}{m}\sum_{i}^{m}(x_i)(x_i)^T, \qquad \Sigma \in \mathbb{R}^{\boldsymbol{n}\times\boldsymbol{n}} \quad (3)$$

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Subsequently, the eigenvectors and eigenvalues of the covariance matrix are obtained through the equation:

$$u^T\Sigma = \boldsymbol{\lambda\mu}, \tag{4}$$

$$\boldsymbol{U} = \begin{bmatrix} | & | & | \\ u_1 & u_2 \dots & u_n \\ | & | & | \end{bmatrix}, \quad u_i \in \mathbb{R}^{\boldsymbol{n}},$$

Consequently, the original data are projected into a k-dimensional subspace, in which the principal eigenvectors of the covariance matrix are selected. These new variables, or principal components, are able to represent the original data and their variance with reduced dimensionality. Each of these new vectors, or components, can be obtained through the expression:

$$x_i^{new} = \begin{bmatrix} u_1^T x^i \\ u_2^T x^i \\ \vdots \\ u_k^T x^i \end{bmatrix} \in \mathbb{R}^{\boldsymbol{k}} \tag{5}$$

Neural networks. Neural networks, in their role as a classification technique, emerged as an ensemble method in which each artificial neuron sought to emulate the behavior of a biological neuron through the combination of a set of weights at its input. This mechanism allowed the neuron to activate and transmit a signal only if the combination of input signals reached a magnitude sufficiently high to surpass a predefined threshold. A wide range of activation functions that could govern the operation of each neuron was identified. However, in the present study, the function $\boldsymbol{ReLU} \rightarrow \sigma = \max(0, \boldsymbol{z})$ as selected for the design of the hidden layers, and the function $\boldsymbol{Softmax} \rightarrow \sigma = e^{z_j}/\sum_i e^{z_i}$ was selected for the output layer, which was required to exhibit binary behavior. Artificial neural networks were established as an ensemble technique in which it was possible to introduce as many input variables as necessary, through a neuron in the input layer that commonly did not include an activation function. Subsequently, as many connections as required were generated, assigning each connection a weight $w_{i,j}$, which was a parameter assigned through the learning process. This allowed the various combinations of inputs to activate, or not, the neurons in the hidden and output layers, enabling each neuron, or combinations of them, to learn nonlinear behaviors from the data. The process of signal propagation in each layer of the neural network is obtained through the expression:

$$\boldsymbol{X}_j = \boldsymbol{W}_{ij} \cdot \boldsymbol{I}, \tag{6}$$

$$\boldsymbol{O}_j = \boldsymbol{activation}(\boldsymbol{X}_j), \tag{7}$$

In this context, $\boldsymbol{X_j}$denotes the matrix of total input signals of the neurons in layer $\boldsymbol{j}$of the neural network, while $\boldsymbol{W_{ij}}$symbolizes the weight matrix of the connections between the current layer $\boldsymbol{j}$and the previous layer $\boldsymbol{i}$. Additionally, $\boldsymbol{I}$is the matrix of input signals and $\boldsymbol{O_j}$represents the matrix of output signals of each layer of the neural network. In order to enable the learning of a neural network, the error in each neuron of the final layer was calculated, $\boldsymbol{eout_k} = \boldsymbol{t_k} - \boldsymbol{o_k}$, by comparing the obtained value $\boldsymbol{o_k}$ with the expected value $\boldsymbol{t_k}$ for each observation $\boldsymbol{t}$. These errors needed to be backpropagated through the neural network via the connections from which each output originated, thus allowing the weights to be updated. Errors can be backpropagated in the neural network using the expression:

$$\boldsymbol{\xi_i} = \boldsymbol{W_{ij}^T} \cdot \boldsymbol{\xi_j}, \tag{8}$$

Where $\boldsymbol{\xi_i}$symbolizes the matrix of errors that were backpropagated to the preceding layer of the neural network, and $\boldsymbol{\xi_j}$refers to the errors originating in the subsequent layer of the neural network. Once the errors were backpropagated through the neural network, these weights were used to allow the neural network to retain information from previous examples and incorporate new information derived from new observations. Gradient descent stood out as one of the most widely used processes for this purpose. One of the processes most commonly employed for this purpose is gradient descent, which is formulated as:

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$$\frac{\partial \xi}{\partial \boldsymbol{W}_{jk}} = \frac{\partial \sum_n (t_n - o_n)}{\partial \boldsymbol{W}_{jk}} = \frac{\partial \xi}{\partial \boldsymbol{O}_k} \cdot \frac{\partial \boldsymbol{O}_k}{\partial \boldsymbol{W}_{jk}} = -2(t_n - o_n) \cdot \frac{\partial \boldsymbol{O}_k}{\partial \boldsymbol{W}_{jk}}, \tag{9}$$

$$\frac{\partial \xi}{\partial \boldsymbol{W}_{jk}} = -2(t_n - o_n) \cdot \frac{\partial}{\partial \boldsymbol{W}_{jk}} \boldsymbol{activation}\left(\sum_j \boldsymbol{W}_{jk} \cdot \boldsymbol{O}_j\right), \tag{10}$$

$$\boldsymbol{W}_{jk}^{(r+1)} = \boldsymbol{W}_{jk}^{(r)} - \boldsymbol{\alpha} \frac{\partial \xi}{\partial \boldsymbol{W}_{jk}}, \tag{11}$$

where $\boldsymbol{W}_{jk}^{(r+1)}$ represents the new updated weight for a connection $\boldsymbol{jk}$, which is updated based on its previous value $\boldsymbol{W}_{jk}^{(r)}$ and the gradient $\partial \xi / \partial \boldsymbol{W}_{jk}$, which provides a new portion of information moderated by the learning-rate hyperparameter $\boldsymbol{\alpha}$[25–27].

3. Results

The designed instrument was applied to a sample of 260 researchers from the four participating universities. In this way, each observation was composed of 23 ordinal variables that were structured as factors, as presented in Table 2, with the objective of enabling the evaluation of the four dimensions of sustainability applied to the educational models of each university. The descriptive statistics for each of the ordinal variables that comprised the survey are presented in Table 3.

Table 3. Descriptive statistics for the ordinal variables of the instrument applied to researchers.

Question	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.	Standard Deviation
Factor 1: Economic Dimension							
p_4	1.000	2.000	3.000	3.188	4.000	5.000	1.1180
p_5	1.000	2.000	3.000	3.069	4.000	5.000	1.1093
p_6	1.000	3.000	3.000	3.342	4.000	5.000	1.1228
p_7	1.000	3.000	3.000	3.327	4.000	5.000	1.0530
p_8	1.000	3.000	3.000	3.427	4.000	5.000	1.0719
Factor 2: Social Dimension							
p_9	1.000	3.000	3.000	3.365	4.000	5.000	1.0945
p_{10}	1.000	3.000	3.000	3.215	4.000	5.000	1.0725
p_{11}	1.000	3.000	4.000	3.535	5.000	5.000	1.1931
p_{12}	1.000	3.000	3.000	3.196	4.000	5.000	1.0708
Factor 3: Environmental Dimension							
p_{13}	1.000	2.000	3.000	3.127	4.000	5.000	1.0954
p_{14}	1.000	2.750	3.000	3.165	4.000	5.000	1.1522
p_{15}	1.000	3.000	3.000	3.223	4.000	5.000	1.0491
p_{16}	1.000	2.000	3.000	3.196	4.000	5.000	1.1097
p_{17}	1.000	3.000	3.000	3.181	4.000	5.000	1.0892
p_{18}	1.000	3.000	4.000	3.758	5.000	5.000	1.1785
Factor 4: Institutional Dimension							
p_{19}	1.000	2.000	3.000	3.119	4.000	5.000	1.0677
p_{20}	1.000	2.000	3.000	3.015	4.000	5.000	1.1689
p_{21}	1.000	3.000	3.000	3.373	4.000	5.000	1.1403
p_{22}	1.00	3.00	3.00	3.15	4.00	5.00	1.0381
p_{23}	1.000	2.000	3.000	3.077	4.000	5.000	1.1227
p_{24}	1.000	3.000	3.000	3.196	4.000	5.000	1.0672
p_{25}	1.000	2.000	3.000	3.112	4.000	5.000	1.1041
p_{26}	1.000	2.000	3.000	3.100	4.000	5.000	1.1379

Next, it was verified whether the collected database contained outlier observations; for this purpose, Mahalanobis distances were employed. This analysis was carried out using the *mahalanobis* function, and a cutoff score of 54.0519 was established based on the χ^2, distribution, considering 99.9% of the distribution as acceptable distances and excluding 0.1% of the observations as outliers. Through this procedure, 18 outlier observations were identified and removed from the database; therefore, the final database consisted of 242 multivariate observations.

With this new treated database, its parametric assumptions were verified, since the selected instrument validation technique was Confirmatory Factor Analysis (CFA), which requires compliance with the assumptions of additivity, normality, linearity, homogeneity, and homoscedasticity. In this way, the first assumption verified was additivity, for which the multivariate correlation matrix was used for each possible pair of ordinal variables. The correlation matrix for the sample used is presented in Figure 1.

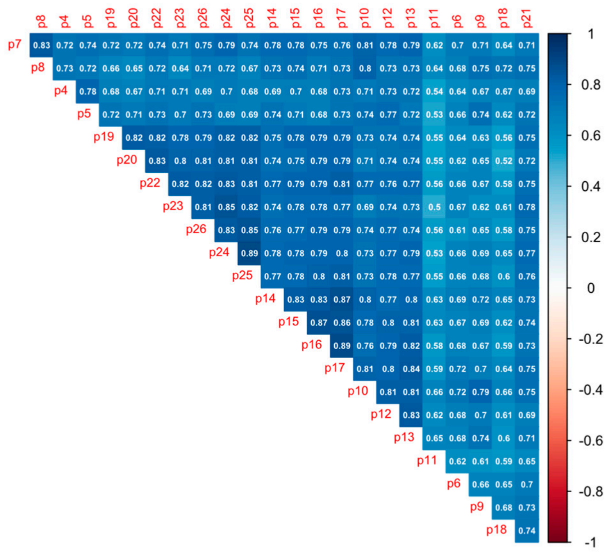
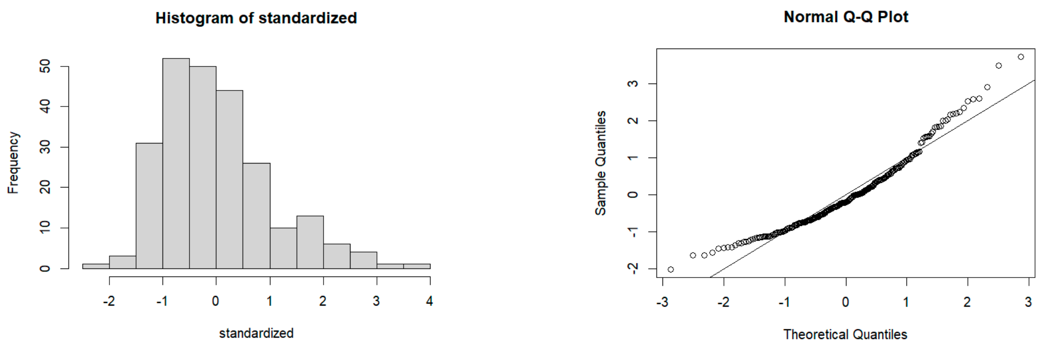
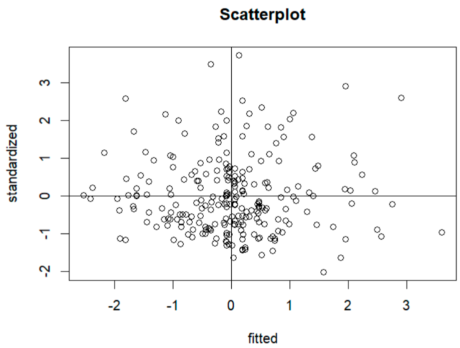


Figure 1. Multivariate correlation matrix for all pairs of variables of the instrument.

As can be observed in Figure 1, when obtaining the bivariate correlation for each pair of questions, all of them reached an adequate correlation value and no pair of questions registered correlation values close to one; therefore, the assumption of additivity was accepted. To verify the assumptions of normality, linearity, homogeneity, and homoscedasticity, false regression analysis was selected as a multivariate technique that uses a set of theoretical random quantiles based on the χ^2 distribution to establish a comparison with the parameters and quantiles of the sample. The results of the false regression analysis are obtained through the histogram, Q–Q plot, and scatter plot presented in Figure 2.



(a) (b)



(c)

Figure 2. Resultados del análisis de falsa regresión, a) histograma, b) Q-Q Plot, c) ScatterPlot.

As can be seen in Figure 2a, when plotting the histogram of the standardized quantiles obtained through the regression model, it was observed that they were distributed uniformly, showing a distribution considerably similar to the normal distribution; therefore, the assumption of normality was accepted. In Figure 2b, the Q–Q plot is presented, where the sample quantiles were plotted against the theoretical quantiles, showing that the quantiles were arranged in a configuration quite close to a 45-degree straight line; thus, the assumption of linearity was accepted. Additionally, Figure 2c presents the scatter plot in which the standardized residuals of the sample were projected against the fitted residuals obtained through the false regression model. Through this procedure, it was observed that none of the quadrants presented an irregular proportion of quantiles relative to the others, and the distances of each quantile from the horizontal axis remained within similar ranges in the interval from −2 to 2. Moreover, no patterns or groupings were observed in the quantiles; therefore, the assumptions of homogeneity and homoscedasticity were accepted.

Once the assumptions were verified in the sample, CFA was applied by configuring its factorial structure using the lavaan library and the R statistical programming language. The results of the CFA are presented in Figure 3 and Table 4.

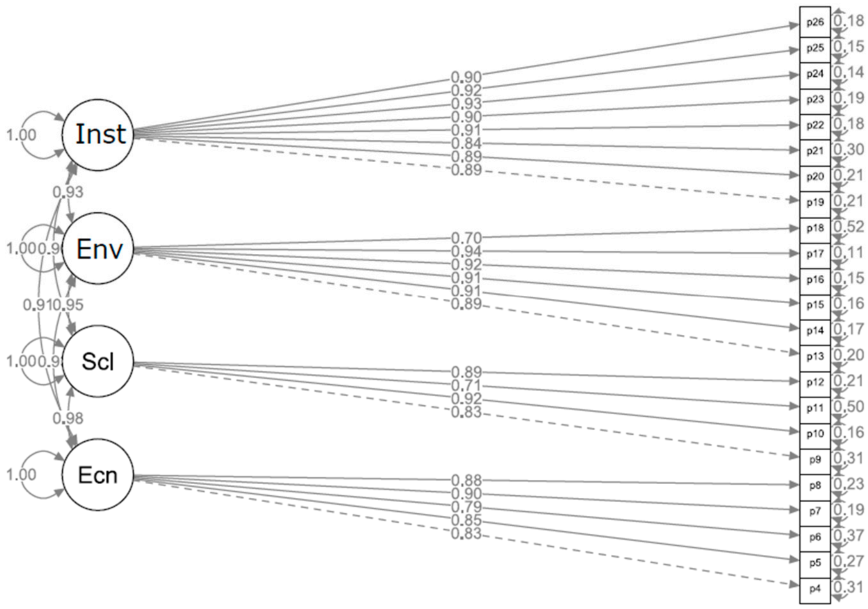


Figure 3. Path diagram for the Confirmatory Factor Analysis applied to the factorial structure.

Table 3. Descriptive statistics for the ordinal variables of the instrument applied to researchers.

npar	fmin	chisq	df	pvalue
52.000	1.294	626.196	224,000	0,000
cfi	**tli**	**nnfi**	**rmsea**	**srmr**
0.944	**0.937**	**0.937**	**0.046**	**0.036**

As can be seen in Figure 3, the factor loadings of each question on its respective factor reached values greater than 0.5; moreover, the correlation among factors did not reach a perfect correlation value. Therefore, it was concluded that there are no indications of invalidity in the factorial structure. In addition, when examining the model goodness-of-fit indices, it was observed that the CFI (Comparative Fit Index), TLI (Tucker–Lewis Index), and NNFI (Non-Normed Fit Index) reached values greater than 0.9; thus, according to the literature [21], the model can be categorized as excellent. Furthermore, when verifying the SRMR (Standardized Root Mean Residual) and RMSEA (Root Mean Square Error of Approximation) indices, values of 0.046 and 0.036 were obtained, respectively, which demonstrates that the instrument used was valid and reliable.

In a complementary manner, CFA allows the estimation of the coefficients of determination r^2 for each question within each factor. These coefficients can be interpreted as the level of influence that each question has in explaining its respective factor. In this way, the coefficients of determination made it possible to identify the components of the instrument that have the greatest impact on each evaluated dimension of the research models with a sustainability focus. The coefficients of determination obtained through CFA are presented in Figure 4.

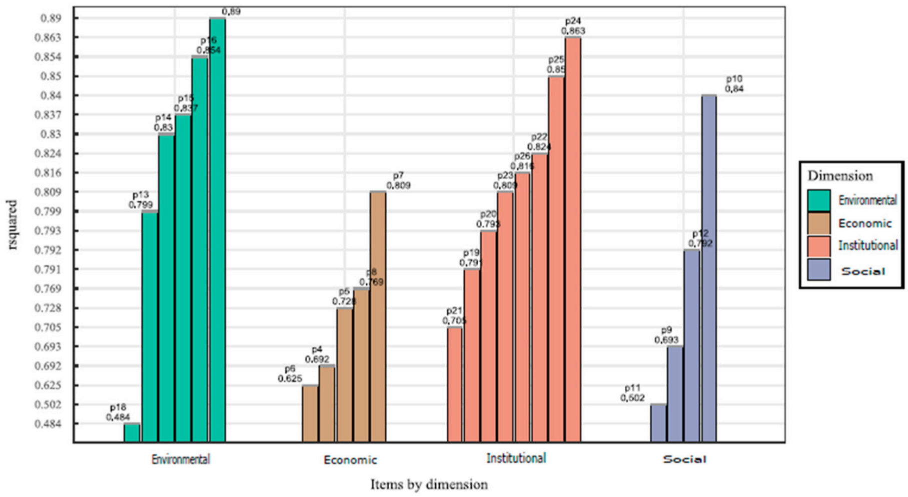


Figure 4. Coefficients of determination r^2 for each question within the dimensions of the factorial structure.

As can be observed in Figure 3, within the environmental dimension, question 17, "there is a significant percentage of research seedbeds that focus their work on the environmental dimension," achieved the highest coefficient of determination, being the one that contributes the most to explaining the variance of that dimension's eta. Similarly, question 7, "the HEI develops a considerable number of *ad honorem* sustainability-related research activities per year," showed the greatest contribution to explaining the variance of the unobserved latent variable "economic dimension." In the institutional dimension, it was observed that question 24, "there is an appropriate number of clubs focused on research and sustainability activities," was perceived as the most important by the surveyed researchers, with a coefficient of determination of 0.863. Finally, in the social dimension, it was evidenced that question 10, "there is an adequate number of departments and/or centers that carry out research activities providing services to society," had the highest determination index, being the most influential for this dimension.

Additionally, as mentioned in [28], these coefficients of determination can be used to create a regression model that allows the extraction of factor scores based on the contributions of each of the questions that compose them. In this way, Equations 12 to 15 were obtained, which allow the calculation of the observed score for each researcher in each dimension:

$$\xi_{económica} = 5.5202(0.692p_4 + 0.728p_5 + 0.625p_6 0.809p_7 + 0.769p_8), \quad (12)$$

$$\xi_{social} = 7.0746(0.693p_9 + 0.840p_{10} + 0.502p_{11} + 0.792p_{12}), \quad (13)$$

$$\xi_{ambiental} = 4.2607(0.799p_{13} + 0.830p_{14} + 0.837p_{15} + 0.854p_{16} + 0.890p_{17} + 0.484p_{18}), \quad (14)$$

$$\xi_{institucional} = 3.1003(0.791p_{19} + 0.793p_{20} + 0.705p_{21} + 0.824p_{22} + 0.809p_{23} + 0.863p_{24} + 0.850p_{25} + 0.816p_{26}), \quad (15)$$

where $\xi_{económica}$, ξ_{social}, $\xi_{ambiental}$ y $\xi_{institucional}$ are the scores for each evaluated dimension of the sustainability-oriented research models of the participating universities, observed for each of their researchers. In this way, the scores for each observation were weighted on a scale from 0 to 100 and were compared with the scores obtained from the real indicators of each institution collected through the research departments of each university. The results are presented in Figure 5.

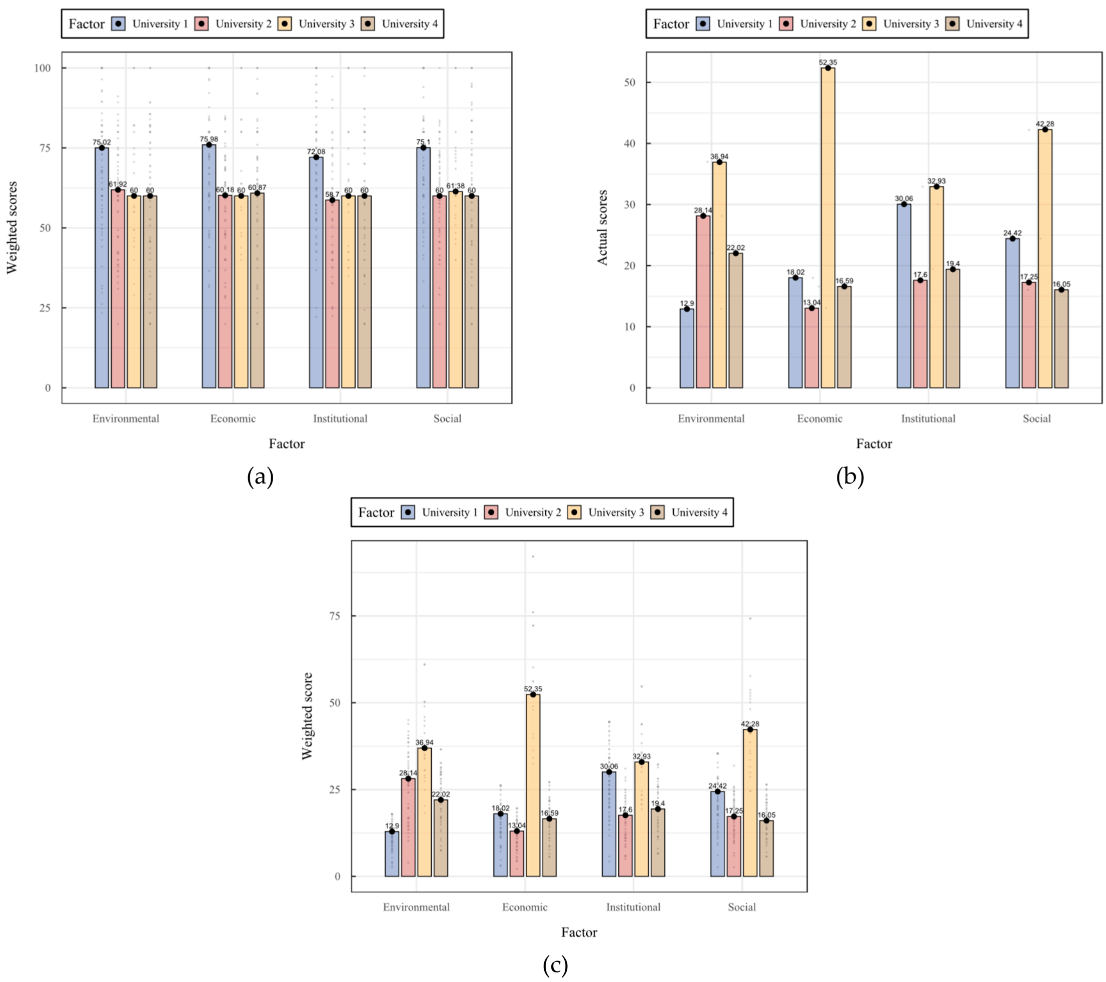


Figure 5. Scores by dimension for each university: (a) scores weighted through CFA, (b) real scores obtained from institutional indicators.

As can be observed in Figure 5, the scores weighted through CFA differ considerably from the scores provided by the research departments of each institution. In this way, it was evidenced that there was a markedly non-linear dependence between the perceptions of researchers at each university and the real indicators of each institution. For this reason, in order to obtain the definitive

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evaluation model for sustainability-oriented university research models, an evaluation model based on neural networks was developed, allowing consideration of the variance in the data obtained through the survey and the non-linear dependence they exhibit with respect to each university's indicators. To this end, the process began by centering and scaling the data for each university and each dimension around the median of each category represented in Figure 5b. In this way, correctly weighted and scaled scores were obtained for each dimension and each university. Verification of the correct centering and scaling of the instrument results is presented in Figure 5c.

Subsequently, a sequential multilayer neural network model was designed to correctly obtain the score for each dimension based on each researcher's responses to the proposed survey. To this end, the dataset was first divided into a training dataset and a testing dataset, where questions p4 to p26 were configured as predictor variables and the scores of the unobserved latent variables for the environmental, economic, institutional, and social dimensions were set as response variables. In this way, a neural network was configured with 26 neurons in its input layer corresponding to the 26 questions of the instrument and 4 neurons in the output layer corresponding to the four unobserved latent variables that reflect the score for each dimension obtained through the neural network.

Subsequently, Principal Component Analysis (PCA) was applied to determine the topology of the neural network, which, as established in [23], can be used to determine the optimal number of hidden layers that the neural network should have. The results of the PCA are presented in Figure 6 and Table 4.

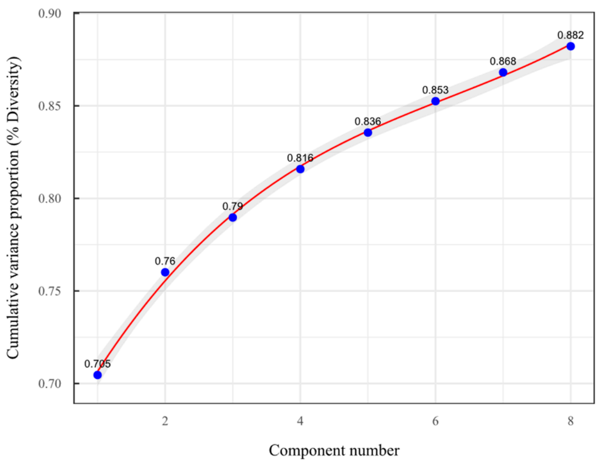

Figure 6. Principal component analysis for the instrument applied to researchers from the participating universities.

Table 4. Results of the principal component analysis for the first five components, performed on the dataset.

Components	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
Standard deviation	4.6190	1.2963	0.9457	0.8899	0.7730
Proportion of variance	0.7045	0.554	0.0295	0.0261	0.0197
Cumulative proportion	0.7045	0.7600	0.8158	0.8158	0.8355

As can be observed in Figure 6 and Table 4, the amount of variance explained by the first component is quite high, reaching a total of 70.45%, which can be explained by a single component. Based on the recommendations of [23], the optimal number of hidden layers that can be used for the design of a neural network is found at the component from which more than 80% of the cumulative variance is exceeded. In this way, the selected optimal number of hidden layers was three, since from the third principal component onward, more than 80% of the variance observed in the dataset is accumulated.

Subsequently, the number of neurons to be included in each hidden layer of the model was verified. For this purpose, the $\boldsymbol{Tensorflow}$ y $\boldsymbol{Keras}$ nd Keras libraries were used, managed

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through the Anaconda environment and interfaced with R via the *reticulate* library. Following the recommendations of [29], it was considered appropriate to use from half to twice the number of neurons in the input layer for the first hidden layer, and similarly for the subsequent layers. In this way, to determine the topology of the first hidden layer of the neural network, 40 neural network models were trained and tested, assigning between 13 and 52 neurons to the first hidden layer, since the number of neurons in the input layer was 26, corresponding to each of the questions of the instrument applied to the 260 researchers from the studied universities. Similarly, 34 deep learning models were trained for the second hidden layer of the neural network, considering options ranging from 11 to 44 neurons; for the third hidden layer, 36 neural networks were trained with configurations ranging from 11 to 46 neurons; and for the fourth hidden layer, 39 models were trained with configurations ranging from 12 to 50 neurons. The results obtained for each of the 149 trained models are presented in Table 5.

Table 5. Performance metrics for each of the designed neural network architectures.

					First hidden layer						
Number of neurons	Loss	Accuracy	loss	Number of neurons	Loss	Accuracy	mse	Number of neurons	Los	Accuracy	mse
13	6.61049	0.52000	143.97343	27	7.64279	0.52000	161.66096	41	7.47758	0.48000	154.70026
14	7.35568	0.56000	161.42709	28	7.74570	0.48000	180.97456	42	6.96407	0.52000	152.56285
15	6.78398	0.48000	152.78194	29	7.99225	0.52000	171.75630	43	7.81216	0.52000	175.81245
16	7.93419	0.52000	175.54967	30	7.54041	0.48000	164.20654	44	7.60679	0.56000	160.68207
17	7.46285	0.56000	163.58923	31	7.49249	0.48000	161.27461	45	7.50052	0.60000	160.53140
18	7.19733	0.44000	158.02576	32	7.43146	0.48000	157.93315	46	7.29040	0.52000	158.58780
19	7.59601	0.52000	155.03230	33	7.23824	0.56000	156.31580	47	7.77413	0.52000	162.27827
20	7.85943	0.48000	177.60406	34	7.45381	0.56000	161.67529	48	7.09082	0.52000	154.42505
21	7.38168	0.56000	153.87184	35	7.64535	0.56000	165.41623	49	7.78823	0.52000	159.25148
22	**6.66107**	**0.60000**	**150.59218**	36	7.38929	0.56000	166.78036	50	8.15013	0.52000	170.45750
23	7.33637	0.48000	163.91420	37	7.67119	0.36000	169.39720	51	7.48246	0.48000	157.51111
24	7.59702	0.52000	168.94106	38	7.46516	0.52000	156.48309	52	7.70194	0.52000	167.40285
25	7.39372	0.36000	156.18542	39	7.58592	0.56000	178.07089				
26	7.58095	0.40000	163.36514	40	7.32193	0.52000	161.51567				
					Second hidden layer						
11	4.4676	0.4846	161.4548	**23**	**4.9649**	**0.7154**	**156.4386**	35	5.8384	0.5615	172.8735
12	5.6191	0.4846	188.0886	24	5.9431	0.5615	202.7327	36	6.0189	0.5615	179.3598
13	4.9793	0.7154	165.7875	25	6.0326	0.5615	199.2739	37	5.3896	0.4846	171.6785
14	4.6691	0.6385	169.0032	26	5.1963	0.4077	179.3626	38	5.5504	0.5615	186.1673
15	5.5874	0.4846	189.8610	27	5.2697	0.6385	183.9680	39	4.7814	0.4846	169.9322
16	5.0036	0.4077	171.2379	28	4.5833	0.4846	157.3014	40	5.8695	0.4846	174.7216
17	4.6083	0.6385	164.4200	29	6.3098	0.7154	177.2449	41	5.3071	0.6385	178.7738
18	5.4634	0.6385	165.2064	30	5.4610	0.4077	169.6887	42	6.1285	0.4077	207.8089
19	5.3136	0.6385	180.4027	31	5.3948	0.4077	175.9713	43	5.0295	0.6385	170.9867
20	6.0081	0.7154	190.3568	32	5.8722	0.5615	189.2480	44	5.1403	0.6385	177.5186
21	5.0952	0.6385	173.8194	33	5.8026	0.7154	179.2200				
22	5.4986	0.6385	172.5228	34	5.5039	0.6385	180.2224				
					Third hidden layer						
11	2.3629	0.5246	94.5119	23	2.0884	0.5246	81.9454	35	2.7750	0.4477	94.2083
12	2.5910	0.6785	100.0968	24	3.1317	0.6015	103.1849	36	1.3735	0.7554	74.2720

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13	2.8406	0.5246	104.8253	**25**	**3.8011**	**0.9092**	**147.5736**	37	2.5664	0.6015	104.5898
14	2.2003	0.7554	95.5288	26	1.4913	0.5246	74.6508	38	2.0267	0.5246	76.5736
15	1.9095	0.6015	73.6238	27	2.3569	0.6015	109.0628	39	3.6870	0.6015	132.1283
16	2.3928	0.6785	77.5403	28	2.6735	0.6785	95.8627	40	3.0592	0.4477	111.4355
17	2.0781	0.6015	60.6476	29	2.4002	0.6785	100.7877	41	2.0472	0.7554	73.2357
18	2.4656	0.6015	102.8611	30	2.4448	0.8323	110.6349	42	3.8664	0.8323	116.6717
19	3.1998	0.6015	116.5262	31	2.7592	0.6015	92.2450	43	2.1354	0.6015	103.2163
20	2.8175	0.6785	101.9881	32	2.7993	0.7554	100.6435	44	2.5400	0.3708	85.3244
21	2.3980	0.6785	81.7346	33	3.0743	0.5246	112.1566	45	2.3946	0.7554	92.1040
22	2.4792	0.5246	107.9653	34	2.4926	0.6785	95.8640	46	2.7339	0.6785	108.8427
Fourth hidden layer											
12	4.9775	0.6385	123.8721	25	7.1137	0.1769	165.8024	38	5.0995	0.5615	139.0243
13	5.3602	0.5615	121.5035	26	7.4176	0.1769	172.9749	39	5.5373	0.6385	145.3960
14	7.0724	0.1769	167.2437	**27**	**5.7623**	**0.7154**	**144.1957**	40	7.8832	0.1769	164.7424
15	5.6259	0.6385	139.3617	28	5.3984	0.4077	144.2599	41	5.7131	0.3308	149.5398
16	5.0447	0.5615	133.7712	29	5.2696	0.4077	127.5835	42	5.4261	0.5615	135.3566
17	5.0504	0.5615	125.1046	30	5.9735	0.1769	139.2516	43	6.0393	0.6385	170.7065
18	7.5365	0.1769	166.0810	31	21.8850	0.3308	667.6537	44	5.7384	0.3308	133.5269
19	4.8958	0.5615	139.3645	32	6.2996	0.6385	143.9705	45	8.6047	0.1769	154.6412
20	4.8681	0.6385	130.3944	33	7.6751	0.1769	163.2600	46	6.9127	0.1769	172.7332
21	4.5606	0.4077	117.0703	34	5.6771	0.5615	159.7961	47	5.4320	0.6385	151.8672
22	11.2039	0.1769	182.3223	35	5.5935	0.6385	125.8826	48	6.3469	0.5615	141.3358
23	5.8319	0.6385	154.5701	36	5.6255	0.5615	161.0143	49	5.7746	0.5615	147.5329
24	5.5590	0.5615	132.3280	37	5.4041	0.7154	151.3845	50	6.3801	0.5615	158.3410

As can be observed in Table 5, among the 149 neural network architectures tested, the architecture with 22, 23, and 25 neurons in its three hidden layers showed the best performance, achieving a loss of 3.8011, an accuracy of 0.9092, and an MSE of 147.5736. All trained models were designed using sequential models through the *keras* library, employing a normalization layer to scale the inputs into an appropriate format. SELU (Scaled Exponential Linear Unit) activation functions were used, along with an L_2-type kernel regularizer with a coefficient $\boldsymbol{l} = 0.001$. In addition, stochastic gradient descent was used as the optimization technique, with a learning rate of 0.1, a momentum of 0.8, and MAE (Mean Absolute Error) as the cost function. With this configuration and 156 training epochs for each model, it was possible to obtain a model capable of predicting, based on the survey, the score of each sustainability dimension with 90.92% accuracy, validated using the validation dataset that was never observed by the model during training.

Additionally, it can be noted that, although the principal component analysis suggested the use of three hidden layers, 39 additional neural networks with different configurations for a fourth hidden layer were implemented. However, it was observed that this fourth hidden layer did not improve accuracy compared to the three-hidden-layer model with the (22, 23, 25) configuration. Therefore, the findings from the PCA were confirmed, and the model with 26 input neurons, 22, 23, and 25 neurons in the three hidden layers, respectively, and 4 neurons in the output layer was selected as the best alternative and is available free of charge for use in the repository: https://github.com/MarcoBurbanoPulles/InvestigationModelEvaluation

The training process of the best models identified for each hidden layer is presented in Figure 7, and the architecture of the best models for each category is presented in Figure 8.

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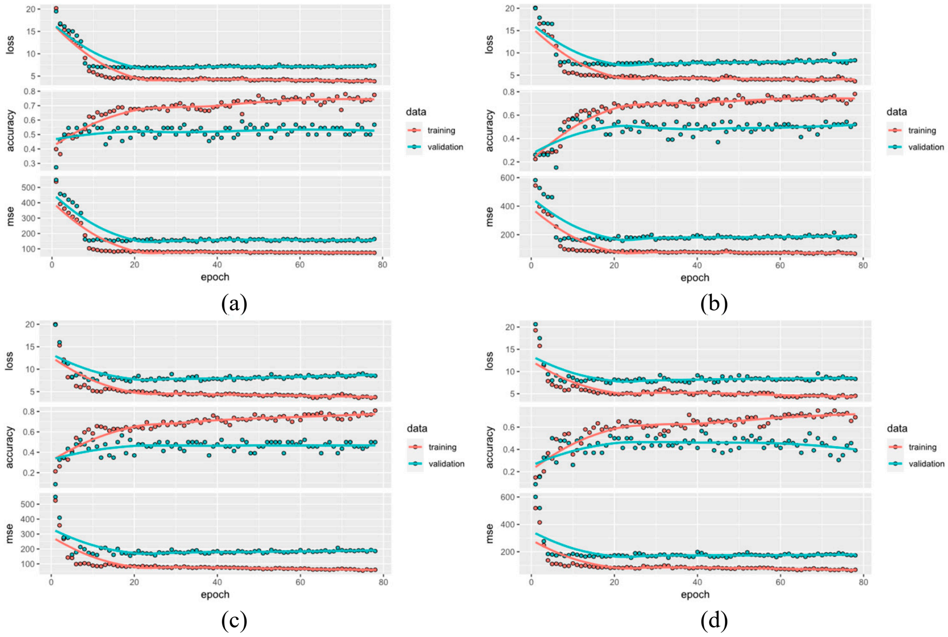
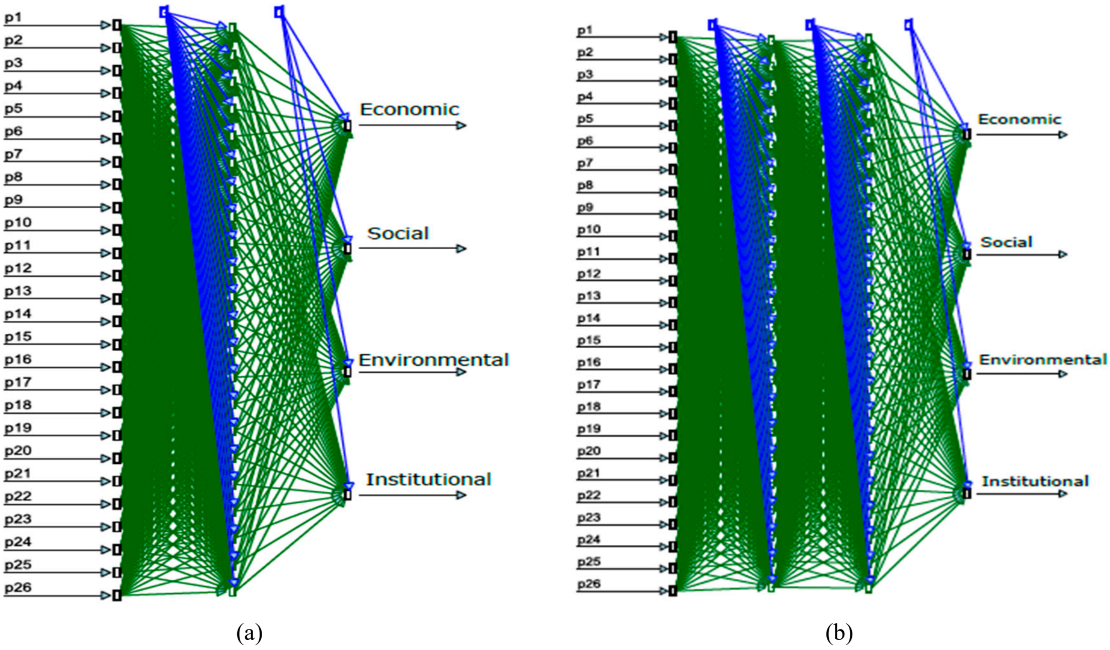


Figure 6. Training process of the best models for each hidden layer: (a) one hidden layer model with 22 neurons, (b) two hidden layer model with 22 and 23 neurons respectively, (c) three hidden layer model with 22, 23, and 25 neurons respectively, (d) four hidden layer model with 22, 23, 25, and 27 neurons respectively.



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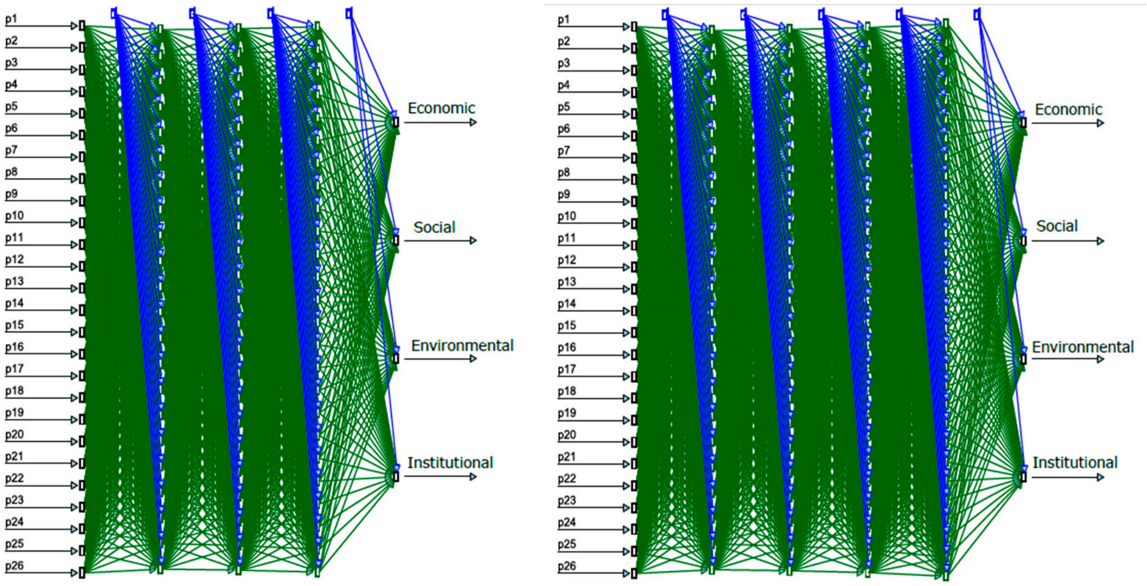

(c) (d)

Figure 7. Architecture of the best trained models for each hidden layer: (a) one hidden layer model with 22 neurons, (b) two hidden layer model with 22 and 23 neurons respectively, (c) three hidden layer model with 22, 23, and 25 neurons respectively, (d) four hidden layer model with 22, 23, 25, and 27 neurons respectively.

4. Discussion

The present study differs significantly from previous related works in several aspects. First, unlike studies [2,30], and [31], which focused on highlighting the importance of university research for sustainable development, this study goes further by proposing and validating a concrete instrument to evaluate university research models in relation to sustainability indicators. In this way, it moves beyond the theoretical level and offers a practical tool that enables an objective diagnosis of the level of sustainability orientation of any higher education institution. Likewise, unlike the purely conceptual study of [32] on smart governance and the institutional analysis of [5] on ecological economics, this work incorporates solid empirical support by applying and validating the proposed instrument in four real universities in Ecuador and Colombia. Similarly, compared to literature reviews such as those in [7] and [33], the theoretical level is surpassed through a quantitative approach involving real participants.

In comparison with previous studies that proposed generic instruments such as those by Findler et al. (2019) and Leal Filho et al. (2018), a distinguishing value of this study is that the developed instrument focuses specifically on university research models, exploring dimensions and indicators designed *ad hoc* for this purpose, rather than being an adaptation of broader multidimensional tools. This allows for a more detailed and relevant evaluation for the specific context of research systems in the IES.

In contrast to the instrument presented by [11] to evaluate environmental education in universities, this research incorporates a more comprehensive perspective by considering four dimensions: environmental, social, economic, and institutional. In this way, research models are evaluated holistically in relation to sustainability. Likewise, unlike the questionnaire focused on infrastructure aspects developed by [12], this study places the emphasis on research activities themselves and their outputs.

Another differentiating element is the robust statistical validation of the instrument through confirmatory factor analysis, regression, principal component analysis, and neural networks. This goes beyond the simple preliminary application of tools proposed in previous studies, providing the current instrument with greater reliability and offering a free, publicly accessible model that can be used to evaluate the research models of multiple universities in the region.

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Regarding the results, a relevant finding was that researchers' perceptions did not correspond to the real indicators reported by the research departments. This motivated the development of a novel evaluation model based on neural networks, which achieved a 90.92% accuracy in predicting the real scores for each dimension. This deep learning model constitutes an important methodological contribution, as it allows the appropriate translation of subjective survey responses into objective scores aligned with the real metrics of each institution.

In this way, through methodological rigor, the proposal and validation of a specific instrument, the incorporation of a neural network model, and a quantitative approach with real participants, this study makes important theoretical and practical contributions. The findings represent an advance over previous research by providing at with an appropriate, free, and effective tool to diagnose and improve sustainability orientation in their respective research models.

5. Conclusions

This study proposed and validated a data-driven framework for assessing the sustainability orientation of research models in Higher Education Institutions, integrating environmental, social, economic, and institutional dimensions. The findings confirm that, although public HEIs show progress in incorporating sustainability principles into their research systems, significant gaps persist between researchers' perceptions and actual institutional performance. These discrepancies highlight the limitations of traditional evaluation approaches and reinforce the need for more robust and analytically grounded sustainability assessment tools.

The multidimensional instrument developed in this research demonstrated strong validity and reliability, as evidenced by excellent goodness-of-fit indices obtained through Confirmatory Factor Analysis. This confirms that the indicators identified through expert judgment effectively capture the core dimensions required to evaluate sustainability-oriented university research models. Moreover, the analysis revealed that specific indicators—such as environmental research seedbeds, ad honorem research activities, research clubs, and units providing services to society—play a critical role in shaping sustainability performance and should be prioritized in institutional strategies.

One of the main methodological contributions of this study lies in the integration of artificial neural networks as a predictive component of the assessment framework. The proposed model achieved a predictive accuracy of 90.92%, demonstrating its capacity to model the non-linear relationships between subjective perceptions and objective institutional indicators. By translating survey data into reliable sustainability performance estimates, the framework overcomes a key limitation in sustainability assessment and provides a practical decision-support tool for university governance.

From a sustainability management perspective, the proposed framework enables Higher Education Institutions to identify performance gaps, prioritize interventions, and support continuous improvement processes in research governance. Its data-driven nature facilitates evidence-based decision-making and enhances institutional accountability in relation to sustainability objectives and the Sustainable Development Goals. Importantly, the framework is scalable and transferable, allowing adaptation to different institutional and territorial contexts beyond the Colombia–Ecuador border region.

Despite its contributions, this study has some limitations. The empirical application focused on a specific regional context and relied on cross-sectional data. Future research could extend the framework through longitudinal analyses, comparative studies across different higher education systems, and the integration of additional sustainability indicators. Furthermore, incorporating other artificial intelligence techniques may further enhance predictive performance and support more advanced sustainability governance models.

This research contributes to the advancement of sustainability assessment methodologies in higher education by offering a validated, data-driven, and practically applicable framework. By bridging measurement, analytics, and decision support, the study supports the development of more resilient, transparent, and sustainability-oriented university research systems, in line with the scope and objectives of *Sustainability*.

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