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Research Trajectories in Latin American Universities: A Multivariate and Plithogenic Analysis of Global Rankings

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Abstract: This study investigates Latin American universities' performance in global rankings through a multivariate, multitemporal approach across the elements of scientific productivity, research influence and internationalization. Subsequently applying HJ- Biplot and clustering analysis reveals the timeliness of differentiated institutional trajectories and the ascendance of structural clusters related to research capacity models. The data are derived from THE and QS rankings and SCImago and comprise the following elements: citations per professor, extremely cited articles, collaboration networks, quantity of grants submitted and more. Conclusions indicate that specific countries and universities of certain types not only yield heterogeneous outcomes but also require targeted measures to promote academic sustainability for the entire region. Moreover, the multivariate perspective provides a replicable methodological perspective by which quality can be measured overtime and its interface with institutional and socio- policymaking. Finally, the research includes Plithogenic Statistics to model the indeterminacy dynamics and disparities that emerge between the variables over time. This method, based on neutrosophic logic, extends the formulation of qualitative evaluations by ranking systems as it assesses worth based on the indeterminacy of university characteristics in Latin America.

Keywords: Multivariate Analysis; University Rankings; Academic Sustainability; Latin America; HJ- Biplot; Scientific Research; Plithogenic Statistics; Neutrosophic.

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1. Introduction

In recent years, university rankings have established themselves as a powerful tool for measuring university quality and facilitating their internationalization in a global context. Despite criticism of their methodologies [1], the rankings have gained popularity among Chilean and Latin American universities, complementing these institutions' own quality assurance mechanisms and indicators. Furthermore, they have become a key information platform for new players in the educational field.

The growing popularity of rankings in Chilean universities highlights their usefulness, but also their need for continuous improvement, since the methodologies used and the indicators selected can generate biased or inaccurate interpretations. The main criticisms of rankings focus on the preeminence of certain indicators, such as scientific production or academic reputation, over others of a qualitative nature, which has revealed regional and cultural gaps between universities globally [1]. To address these ambiguities inherent to rankings, this study incorporates Plithogenic Statistics, a neutrosophic approach that models the truth, falsity, and indeterminacy of indicators, allowing for a more complete assessment of the dynamics of university performance in Latin America.

The liberalization of national borders, resulting from a new phase of globalization, has given rise to a highly competitive higher education market dominated by the research-oriented university model [2-3]. This model has generated significant gaps in Latin America due to the low volume of scientific production compared to regions such as North America, Europe, and Asia. However, many Latin American universities are transitioning from a teaching-centered approach to one with a greater emphasis on scientific research, addressing the challenges of this global market.

In this context, this article reflects on the role of rankings in the quality assurance processes of Chilean universities and their implications for the Latin American case. To achieve this objective, the characteristics of the main university rankings, such as the World University Rankings, will first be described. University Ranking (THE), the ARWU (Shanghai Academic Ranking of the World University), the Quacquarelli Symonds (QS), the SCImago, and the Leiden Ranking (CWTS). Secondly, the relevance of rankings as institutional assessment tools in the region will be analyzed. Thirdly, the strategic importance of research for university sustainability will be demonstrated. Finally, regional gaps in university competitiveness will be highlighted, complemented by a plithogenic analysis that addresses the indeterminacies and contradictions between indicators, offering an innovative perspective for understanding the trajectories of Latin American universities on the global stage.

1.1. University Rankings

In this section, we will briefly describe the origin of rankings, analyze their main characteristics, and compare their indicators. We will also critically examine the methodologies used, noting their advantages and disadvantages.

1.1.1. Shanghai Academic Ranking of World Universities

The first university ranking was carried out by Shanghai University in 2003. Initially, the ARWU ranking was designed to examine the main characteristics of the world's best universities and to provide relevant information to adapt the Chinese university system to international quality standards [4]. While ARWU was the first ranking of the 21st century, there are precedents in the measurement of universities carried out by Jack Gorman between 1967 and 1983. However, the diffusion that the ARWU ranking achieved (mainly thanks to the Internet [5]) was only achieved in the 21st century.

Unlike other rankings such as THE or QS, the ARWU ranking compiles information from databases independent of those provided by universities. It primarily uses hard data (number of Nobel Prizes, Fields Medals, number of citations, among other indicators) (see Table 1). In this sense, the methodology employed by ARWU has been criticized for its overemphasis on these indicators to the detriment of those linked to qualitative dimensions, in addition to the bias generated by focusing on Nobel Prize and Fields Medal winners. Indeed, critics of the rankings have argued that "more important than having indicators for world-class universities (...) is ensuring that there are good medical schools and good training programs for agronomists and educators to guarantee an adequate level of human and social capital" [2] (p. 274).

Table 1. Indicators and weights of the ARWU Ranking.

Dimension	Indicator	Code	Weights
Quality of Education	Nobel Prize and Fields Medal Winning Alumni	Alumni	10%
Teacher quality	People who win Nobel Prizes and Fields Medals	Grant	20%
	Highly Cited Researchers	HiCi	20%

Research results	Articles published in Nature and Science	N&S	20%
	Articles indexed in SCIE and SSCI	PUB	20%
Size of the institution	Academic performance per capita of an institution	PCP	10%

Source: [9].

1.1.2. World University Rankings (WURR)

This ranking was created in 2010 and, unlike the ARWU ranking, uses opinion polls as its methodology. It was created by the English magazine Times Higher Education in 2010 and is published annually. Unlike the ARWU, this ranking has specific classifications in different areas of knowledge and uses information submitted by the universities themselves. The ranking's methodology has been criticized for using the number of citations accumulated by a university (more than 200 citations) as an exclusion criterion. At the same time, it excludes universities that do not have undergraduate students (i.e., research centers and graduate study centers). Likewise, it fails to consider the specificities of each field of knowledge in terms of publication and citation volume. For example, the volume of citations is much higher in Business Studies than in disciplines such as History. Furthermore, it fails to differentiate between the sources of funding at institutions in relation to research. According to its critics, it continues to reproduce the gap between the wealthiest countries compared to the poorest regions.

Table 2. Indicators and weights of the THE Ranking.

Dimension	Weights	Indicator	Worth
Teaching	30%	Teaching reputation	15%
		Staff-student relationship	4.50%
		Relationship between doctorates and bachelor's degrees	2.25%
		Relationship between awarded doctorates and academic staff	6%
		Institutional income	2.25%
Investigation	30%	Research reputation	18%
		Research income per professor	6%
		Research productivity	6%
Quotes	30%	Quotes	30%
International perspective	7.50%	Proportion of international students	2.50%
		Proportion of international staff	2.50%
		International collaboration	2.50%
Industry	2.50%	Industry revenues	2.50%

Source: [9].

Regarding the measurement of teaching quality, the THE ranking measures it through the university's reputation (using surveys administered to academic staff) and the faculty-student ratio, both for graduates and PhDs. In fact, as can be seen in Table 2, the reputation survey carries more weight than the other quality indicators.

1.1.3. QS World University Rankings

This ranking began publishing in 2009 by the British organization QS World University Ranking. Its measurement uses three sources of information: faculty opinion surveys, scientific productivity (measured through the Scopus database), and information provided by the universities themselves. Like the ranking, it has specific indicators linked to different areas of knowledge. However, the academic reputation indicator has the highest score in this ranking compared to its counterparts already described (see Table 3).

Table 3. QS Ranking indicators and weights.

Indicator	Weights
academic reputation	40%
employer's reputation	10%
Teacher-student relationship	20%
Research citations per article	20%
International staff	5%
international students	5%

Despite the relative advantages of this ranking compared to ARWU, its critics continue to highlight the marked subjectivity of the opinions of academics and employers when measuring the prestige and reputation of universities. Similarly, authors such as Barsky [6] and Marginson [7] consider QS to be less detailed and complex than the ranking. However, along with SCImago, QS has a specific ranking to measure the scientific output of Latin American institutions.

1.1.4. SCImago

This ranking was created in 2009 by a group of Spanish universities (SCImago Research Group). Its main objective has been to measure research-oriented institutions and their volume of scientific output. Both SCImago and QS have rankings that measure research output. In addition to measuring each institution's research output, SCImago evaluates innovation and dissemination through the number of publications and citations (among other metrics). Like QS, the SCImago index has a specific ranking for Latin America that measures the research output of universities in the region. Therefore, when constructing specific rankings for Latin America, these rankings have considered the gap between European, Asian, and North American universities in terms of volume of scientific output.

1.1.5. Leiden World Ranking

Like the SCImago ranking, the Leiden World Ranking focuses exclusively on scientific production. Its impact assessment method is based on bibliometric indicators (Clarivate-Web of Science) that measure the number of publications and citations per university. Its first version was published in 2007, and critics have argued that this ranking should better specify the characteristics of publication-based scientific measurement, since, for example, a full-length research study would have a bibliometric value similar to that of a review [8]. Likewise, the evaluative use of this ranking of databases, originally created as storage and dissemination tools, has been criticized [8]. Nevertheless, this ranking constitutes a reference for the methods used to evaluate the impact of indexed research worldwide.

1.2. University rankings as international evaluation tools

As we have mentioned, the diversity of rankings created to date provides universities in the region with conceptual and methodological tools that allow them to measure and evaluate their performance. The assessment tools offered by the rankings have introduced a new field of university quality evaluation, adding to the quality assurance mechanisms developed by the universities themselves, as well as to the legal framework that regulates the quality of educational services provided by the country's universities. In fact, the various indicators included in the rankings have been integrated into the university strategic plan, demonstrating the impact they have had on the governance of higher education institutions in recent years.

Most private universities have evolved from institutions focused on teaching and undergraduate training to institutions with a strong research orientation. In this sense, rather than considering that an effective institutional policy aimed at promoting research would allow them to rise in the rankings and influence other areas (such as internationalization, reputation, and stakeholder engagement), increasing universities' research capacity aligns with international political agendas regarding the promotion and development of scientific production. Furthermore, many scholars have considered that a solid scientific infrastructure lays the foundation for social development projects. Therefore, scientific research and development constitute a mechanism that would enable the link between society and the university, fulfilling one of the pillars of the university's role in supporting the scientific development of countries.

1.3. The Latin American regional gap

Latin American universities are further from the top positions in international rankings. Ruiz has stated that they "show Latin America's disadvantage compared to the world (...) depending on the classification system analyzed, this region could be less favored than others" [9] (p. 143). For example, the absence of Latin American universities in the university rankings created by Shanghai University is due to the use of a biased methodology that emphasizes specific dimensions of university functioning but makes invisible other dimensions of the institution's corporate functioning, which are equally relevant, since they are linked to the cultural and social context of each country [9].

According to Ruiz's research [9], the position achieved by the region's universities is consistent with and related to the level of investment in science and education of the host countries, which is low compared to that of countries in other regions such as Europe or Asia. For example, Brazilian universities lead the specific rankings and appear in better positions in the general ones, which could reflect state investment and the wealth of the country itself.

In short, one of the pillars of university success in the global market is the level of investment that countries are willing to make. This idea demonstrates that structural conditions exogenous to universities themselves determine and limit their growth, functioning, and the institutional model they desire to achieve.

2. Materials and methods

This study analyzed Latin American university rankings from 2020 to 2025, with the aim of identifying clustering patterns based on their research performance. To this end, only those institutions that provided complete information on the variables associated with research output were considered, applying two configurations: one cluster based on four variables and another based on five, incorporating the proportion of academic staff with doctorates. As a result of the filtering and classification process, clusters of 125 and 137 institutions were formed, respectively, allowing for a more precise characterization of the research landscape at Latin American universities.

2.1. Cluster analysis

Hierarchical cluster analysis (HCA) is a statistical technique that allows a set of observations to be grouped into homogeneous clusters, such that the elements within the same group are more similar to each other than to those of other groups [10]. Among the hierarchical linkage methods, Ward's method stands out for its approach based on minimizing the internal variance of the clusters [11].

Ward's method uses a merging criterion to minimize the reduction in the total sum of squares within clusters. At each clustering stage, the two clusters whose combination produces the smallest possible increase in intra-cluster variance are merged [12]. This ensures that the clusters formed are internally compact and well-defined.

Formally, the optimization function that Ward minimizes corresponds to

$$\Delta E = \frac{n_1 n_2}{n_1 + n_2} \left|\left|c_1 - c_2\right|\right|^2 \quad (1)$$

Where

- $n_1$and $n_2$represent the sizes of the clusters to be merged.
- $c_1$and $c_2$are the vectors of their respective centroids.
- $\left|\left|c_1 - c_2\right|\right|^2$is the squared Euclidean distance between the centroids.

This criterion ensures that the chosen merger increases the internal heterogeneity of the data set as little as possible.

2.2. Principal component analysis

Principal Components Analysis (PCA) is a dimensionality reduction technique that transforms a set of possibly correlated variables into a new set of uncorrelated variables, called principal components. The goal is to capture as much of the data's variance as possible in as few components as possible.

Given a multivariate data set represented by a matrix, where $X \in R^{IxJ}$ I is the number of individuals and J is the number of variables, the standard procedure implies:

1. To center the data: Subtract the mean from each variable.
2. To calculate the variance-covariance matrix S, alternatively, the correlation matrix.
3. To perform the spectral decomposition of $S = V\Lambda V^T$
   where:
   - Vcontains the eigenvectors (principal directions),
   - ΛIt is a diagonal matrix of eigenvalues (variance explained by each component).
4. Project the data onto the subspace defined by the first principal components to obtain a lower-dimensional representation that retains as much information as possible.

Each eigenvalue $\lambda_j$represents the amount of variance explained by the principal component j, and the proportion of variance explained by the first k components is calculated as:

$$\frac{\sum_{j=1}^{k} \lambda_j}{\sum_{j=1}^{J} \lambda_j} \quad (2)$$

This establishes the mathematical basis for multivariate analysis using HJ-Biplot.

2.2. Multivariate analysis using HJ-Biplot

The HJ-Biplot, developed by Galindo [13], is a multivariate analysis methodology that optimizes the simultaneous representation of individuals and variables in a reduced-dimensional space, usually two-dimensional. It arises as an extension and improvement of the traditional Biplot proposed by Gabriel [14]. Mathematically, from a centered data matrix $X \in R^{IxJ}$, where Iμ is the number of individuals and Jμ is the number of variables, a singular value decomposition (SVD) is performed:

$$X = UDV^T \quad (3)$$

Where:

- Ucontains the singular vectors on the left (associated with individuals)
- Vcontains the correct singular vectors (associated with variables)
- DIt is a diagonal matrix with ordered non-negative singular values.

The HJ-Biplot assigns to:

- The individuals:$A = UD$
- The variables:$B = VD$

This mapping ensures the highest quality of joint representation of individuals and variables in the same graph. These visualizations allow variables to be interpreted through vectors or arrows pointing in the direction of growth of the variable, and the length of the variable represents its variability, indicating that angles close to 0° or 360° present strong direct correlations. Those close to 180° present strong inverse correlations, and angles close to 90° present independence. Furthermore, individuals will be better represented by a variable the closer they are to the vector that represents it, and orthogonal projections to them can provide a reference of the value above or below the mean in terms of the proportion of the standard deviation. In addition, the proximity between individuals (similarity) is visualized [15].

An important extension is the dynamic HJ-Biplot, which allows to visualize multivariate data evolving over time or under different conditions. This variant is implemented in R by combining the tkrplot and dynBiplotGUI packages. The tkrplot package allows to render interactive graphs in dynamic windows. On the other hand, dynBiplotGUI creates a graphical interface to select analysis periods and dynamically represent the trajectories of individuals or variables over time [16][17].

With this tool, you can analyze structured data in three ways (individual, variable, and temporal), selecting time intervals and observing how their relative positions change. This is especially useful in longitudinal studies.

2.3. Plithogenic Statistics (PS).

Plithogenic Statistics (PS) is an advanced methodological framework that allows for the integration and analysis of diverse data, overcoming the limitations of traditional statistical techniques. While conventional methods typically examine variables in isolation, PS explores the complex interrelationships between multiple factors, offering a deeper understanding of the studied phenomena. This versatility makes it valuable in fields such as pedagogy, applied economics, and biomedical research [18].

In the educational field, PEs are especially useful for assessing the impact of pedagogical innovations, as they allow for analyzing how different elements (student performance, teacher development, etc.) interact and how they collectively influence academic outcomes. This approach reveals patterns that would otherwise go unnoticed with traditional methodologies, providing key information for designing more effective educational strategies.

One of the greatest strengths of PEs is their ability to combine quantitative data (such as test scores) with qualitative information (such as teacher and student perceptions), generating a more complete assessment of educational processes [19]. Furthermore, their ability to process large volumes of data and detect complex relationships is crucial in the analysis of educational policies, where effects can manifest directly and indirectly in multiple dimensions.

PEs also facilitate the personalization of educational strategies by identifying specific patterns in different groups, allowing for more precise interventions tailored to diverse educational contexts [20]. However, their implementation is not without challenges, as they require specialized knowledge in advanced analytics and a significant investment in data collection and processing. Even so, their potential to improve the understanding of educational systems justifies these efforts [21].

In conclusion, EPs represent a powerful tool for the study of pedagogical phenomena, offering valuable elements for educational decision-making. Despite their technical challenges, they have established themselves as an indispensable resource for researchers and planners committed to academic excellence [20].

Plithogenic Statistics (PS) encompasses the analysis and observations of the events under study. It allows for the analysis of many output variables that are neutrosophic or indeterminate.

Subclasses of Plithogenic Statistics (EP)

Statistics **(PS)** encompasses various specialized methodologies that expand the analytical capabilities of complex scenarios. Its main subclasses include:

1. **Multivariate Plithogenic Statistics** – Analyzes multiple variables simultaneously, identifying patterns and correlations in multidimensional data sets.
2. **Plithogenic Neutrosophic Statistics** – Incorporates Neutrosophic (logic that considers true, false, and indeterminate) to handle inaccurate or contradictory information.
3. **Plithogenic Indeterminate Statistics** – They work with incomplete or uncertain data, allowing robust inferences despite ambiguity.
4. **Plithogenic Intuitionistic Fuzzy Statistics** – Combines fuzzy and intuitionistic logic to model degrees of membership and non-membership in fuzzy sets.
5. **Fuzzy Statistics of Plithogenic Images** – Applied in image processing, they analyze visual information with diffuse and overlapping components.
6. **Plithogenic Spherical Fuzzy Statistics** – Uses spherical fuzzy sets to represent data in multidimensional spaces with degrees of uncertainty.
7. **Fuzzy Extension Plithogenic Statistics (general)** – Covers all variants that integrate fuzzy logic to handle inaccuracies in data analysis.

These subclasses allow **EPs to be adapted** to different contexts, from artificial intelligence to social sciences, improving the interpretation of phenomena with high levels of complexity and uncertainty.

In a neutrosophic population, each element has a triple probability of affiliation (T_j, I_j, F_j), where $T_j, I_j, F_j \in [0,1]$ like that $0 \le T_j + I_j + F_j \le 3$.

If we assume that we must have the data set (T_j, I_j, F_j) for $j = 1, 2, \dots, n$, where n is the sample size, then the average probability of all the data in the sample is calculated by Equation 4.

$$\frac{1}{n}\sum_{j=1}^{n}(T_j, I_j, F_j) = \left(\frac{\sum_{j=1}^{n} T_j}{n}, \frac{\sum_{j=1}^{n} I_j}{n}, \frac{\sum_{j=1}^{n} F_j}{n}\right) \quad (4)$$

In this investigation, we also consider some operations in the form of *neutrosophic numbers.* These ways of representing indeterminacy are, under certain conditions, equivalent to working with intervals.

Definition 1: ([21-22]) A *neutrosophic number* N is defined as a number as follows:

$$\mathrm{N} = \mathrm{d} + \mathrm{I} \quad (5)$$

Where d is called *the determinate part* and I is called *the indeterminate part.*

Given $\mathrm{N}_1 = \mathrm{a}_1 + \mathrm{b}_1\mathrm{I}$ and $\mathrm{N}_2 = \mathrm{a}_2 + \mathrm{b}_2\mathrm{I}$ They are two neutrosophic numbers, some operations between them are defined as follows:

$\mathrm{N}_1 + \mathrm{N}_2 = \mathrm{a}_1 + \mathrm{a}_2 + (\mathrm{b}_1 + \mathrm{b}_2)\mathrm{I}$ (Addition);

$\mathrm{N}_1 - \mathrm{N}_2 = \mathrm{a}_1 - \mathrm{a}_2 + (\mathrm{b}_1 - \mathrm{b}_2)\mathrm{I}$ (Difference),

$\mathrm{N}_1 \times \mathrm{N}_2 = \mathrm{a}_1\mathrm{a}_2 + (\mathrm{a}_1\mathrm{b}_2 + \mathrm{b}_1\mathrm{a}_2 + \mathrm{b}_1\mathrm{b}_2)\mathrm{I}$ (Product),

$\frac{\mathrm{N}_1}{\mathrm{N}_2} = \frac{\mathrm{a}_1+\mathrm{b}_1\mathrm{I}}{\mathrm{a}_2+\mathrm{b}_2\mathrm{I}} = \frac{\mathrm{a}_1}{\mathrm{a}_2} + \frac{\mathrm{a}_2\mathrm{b}_1-\mathrm{a}_1\mathrm{b}_2}{\mathrm{a}_2(\mathrm{a}_2+\mathrm{b}_2)}\mathrm{I}$ (Division).

Furthermore, arithmetic operations between intervals are important in this document, which are summarized below ([23]):

Given $\mathrm{I}_1 = [\mathrm{a}_1, \mathrm{b}_1]$ and $\mathrm{I}_2 = [\mathrm{a}_2, \mathrm{b}_2]$ We have the following operations between them:

$\mathrm{I}_1 \le \mathrm{I}_2$ if and only if $\mathrm{a}_1 \le \mathrm{a}_2$ and $\mathrm{b}_1 \le \mathrm{b}_2$.

$\mathrm{I}_1 + \mathrm{I}_2 = [\mathrm{a}_1 + \mathrm{a}_2, \mathrm{b}_1 + \mathrm{b}_2]$ (Addition);

$\mathrm{I}_1 - \mathrm{I}_2 = [\mathrm{a}_1 - \mathrm{b}_2, \mathrm{b}_1 - \mathrm{a}_2]$ (Subtraction),

$\mathrm{I}_1 \cdot \mathrm{I}_2 = [\min\{\mathrm{a}_1\cdot\mathrm{b}_1, \mathrm{a}_1\cdot\mathrm{b}_2, \mathrm{a}_2\cdot\mathrm{b}_1, \mathrm{a}_2\cdot\mathrm{b}_2\}, \max\{\mathrm{a}_1\cdot\mathrm{b}_1, \mathrm{a}_1\cdot\mathrm{b}_2, \mathrm{a}_2\cdot\mathrm{b}_1, \mathrm{a}_2\cdot\mathrm{b}_2\}]$ (Product),

$\mathrm{I}_1/\mathrm{I}_2 = \mathrm{I}_1\cdot(1/\mathrm{I}_2) = \{a/b: a\in\mathrm{I}_1, b\in\mathrm{I}_2\}$, always that $0 \notin \mathrm{I}_2$ (Division).

3. Results

3.1. Segmentation of 4 variables and 137 institutions

According to the segmentation presented in the methodology, four variables were considered for this initial analysis, which yielded 137 institutions with values. Imputation was avoided to improve the quality of representation and estimate bias. Figure 1 therefore presents the dendrogram of the cluster analysis. The final merger structure reveals two large groups, but visually, there are four groups with reasonable distances for establishing the clusters. Therefore, a four-segment analysis and a general analysis are proposed.

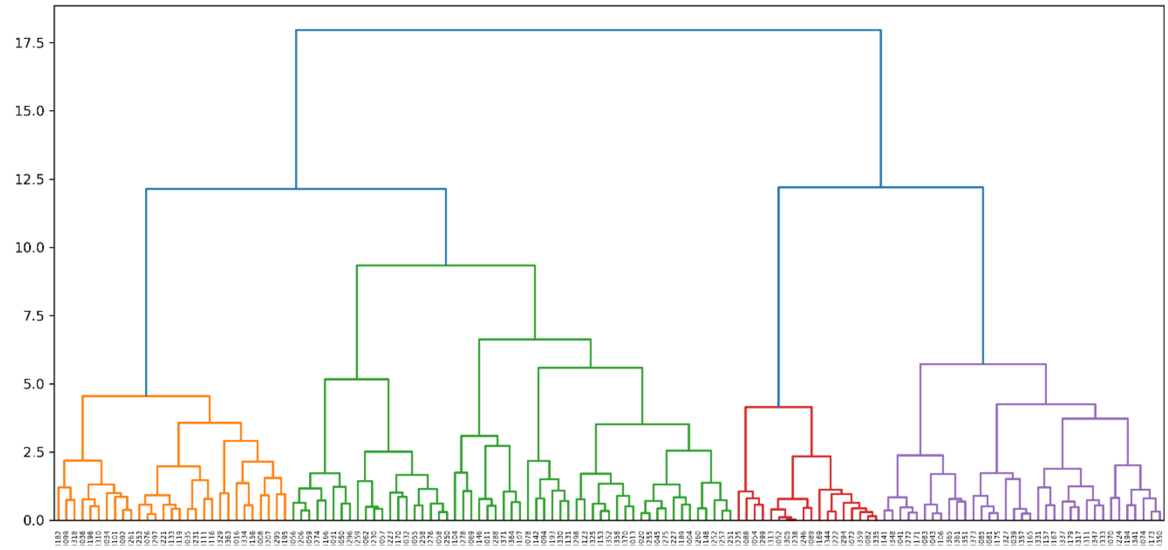

Figure 1. Segmentation of the dendrogram of four variables and 137 institutions.

Table 4 shows the distribution of institutions grouped by country and group. In Group 4, Brazilian and Chilean institutions predominate. Therefore, these are the most influential and have the greatest presence at the top of the ranking, suggesting that this group is the most represented.

Table 4. Distribution by country segmentation of four variables and 137 institutions.

Country	Group 1	Group 2	Group 3	Group 4	Total
Argentina	7	12			19
Bolivia		1			1
Brazil	2	3	9	28	42
Chili		6	6	7	19
Colombia	4	6	3		13
Costa Rica	2	1			3
Cuba	1	1			2
Ecuador	1	4			5
Mexico	8	13			21
Paraguay	1				1
Peru	1	3			4
Puerto Rico		1			1
Uruguay	2	1			3
Venezuela		3			3
Total	29	55	18	35	137

The following is a general analysis, and there is also an analysis segmented by groups to evaluate the influences of the variables of the international classifications according to the segment analyzed. Figure 2 shows the dynamic HJ-Biplot of 4 variables covering the 137 institutions in the analysis. The dynamics are observed with a 90% inertia filter to visualize the largest movements of institutions and with a 0% inertia filter on the variables. In addition, more than 78% of the observed variance is absorbed, which ensures a very good visualization quality.

It is shown that the variables of *papers per faculty* and *citations paper* have a high correlation and a very similar dynamic throughout the years of analysis. Moreover, a high correlation is observed in 2023, which has decreased over the last years.

On the other hand, it is verified that the institutions Universidad Federal de São Paulo, Universidad Federal do ABC, Universidad Federal do Rio Grande, Universidad de La Frontera (UFRO), and Universidad de La Habana report the highest dynamics of movement with respect to the associated filters, focusing on values close to the mean without many variations or predominance.

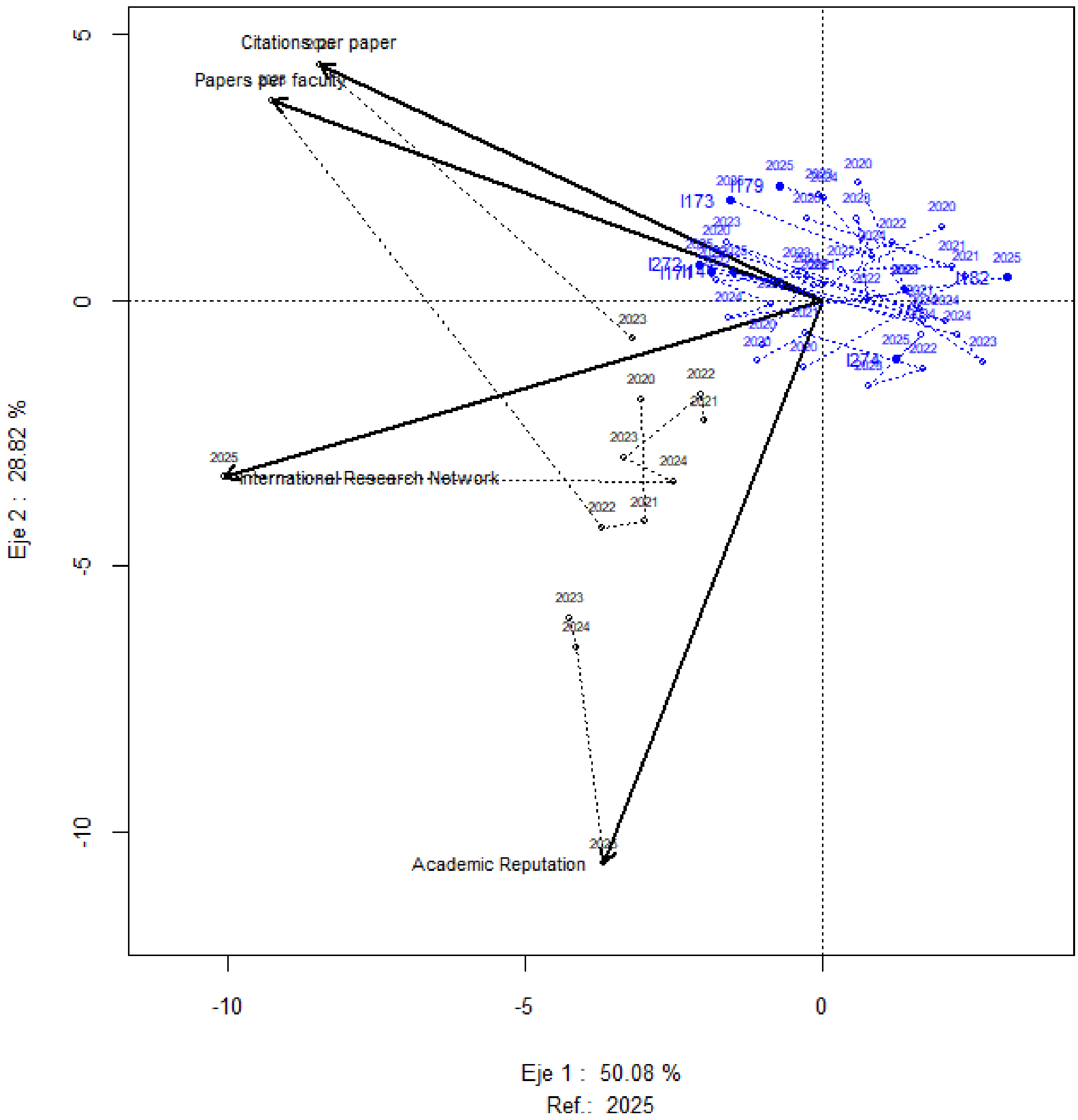

Figure 2. General HJ-Biplot analysis with four variables.

Figure 3 shows the HJ-Biplot representation of the multivariate data corresponding to each of the four clusters indicated at the beginning of this section, showing how the dynamics of the variables differ according to each cluster.

Variance absorptions greater than 70% are observed in all clusters except the first group, indicating high variability with lower representation quality but maintaining acceptable parameters.

It should be noted that, in the first and second groups, the variables of academic citations and scientific publications show practically no correlation, demonstrating the different parameters of this group in the analysis of their publications. Furthermore, clear heterogeneity is detected around these two values, with no variable standing out in the representation of the institutions displayed. Furthermore, a strong inverse correlation is evident between academic reputation and indicators of research productivity and quality in these groups. This raises a debate about the parameters used by international academics participating in these surveys to define a higher education institution with a good reputation.

Furthermore, in Clusters 3 and 4, the correlations between research-related variables are more clearly observed. The distribution of institutions in Cluster 4 is more homogeneous, showing high variability and robust correlations between indicators of research productivity and quality, on the one hand, and, on the other, indicators of reputation and international research network. The latter is what would encompass the most prestigious and internationally recognized institutions, especially in Cluster 3, where institutions remain among the top 80 in the ranking.

Additionally, atypical data are observed from the third cluster, such as the Adolfo Ibáñez University (I088) and the National University of Colombia (I225), which are well below average in research indicators.

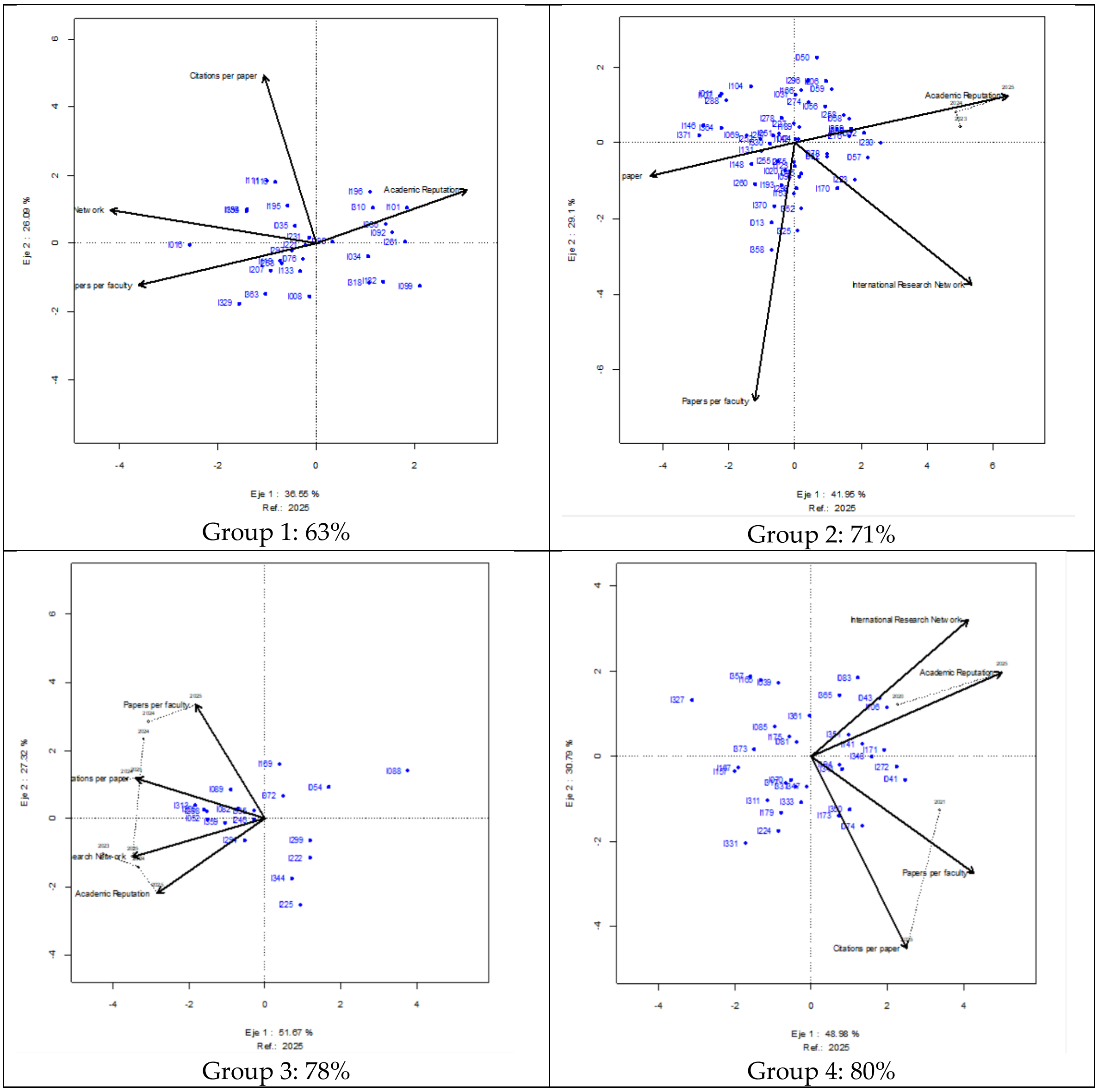

Figure 3. HJ Biplot by cluster, reference 2025.

3.1. Segmentation of 5 variables and 125 institutions

According to the segmentation shown in the methodology, five variables were considered for the second analysis, resulting in 125 institutions with values, to which the variable of faculty with doctorates was added. Figure 4 illustrates the dendrogram from the cluster analysis, showing that the final merger structure conglomerates two large groups, but visually, four groups are observed with reasonable distances to establish the clusters.

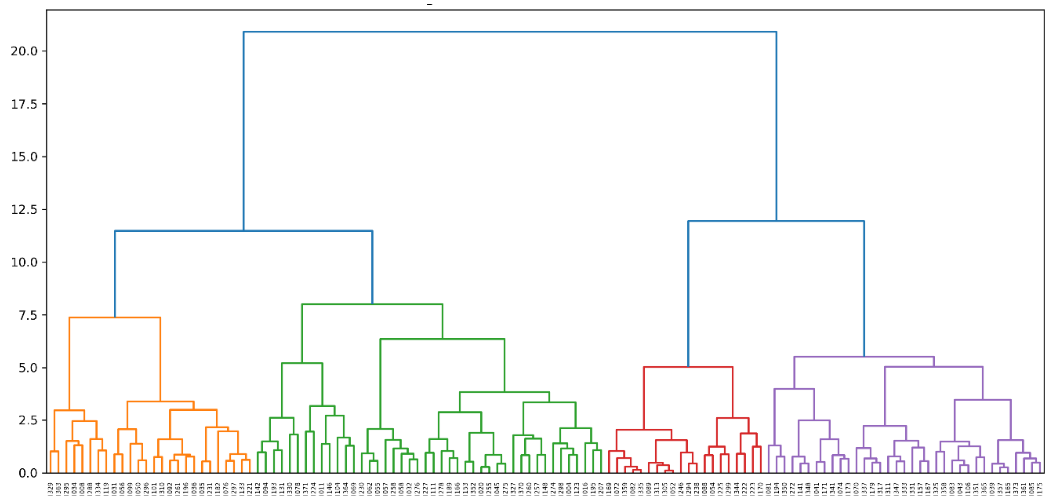

Figure 4. Segmentation of the dendrogram with five variables and 125 institutions.

Table 5 shows the distribution of institutions grouped by country and group. Group 4, composed of Brazilian and Chilean institutions, predominates. These are the most influential and have the greatest presence at the top of the ranking. The second group, in turn, has the largest number of institutions, demonstrating the presence of this profile in the Latin American ranking.

Table 5. Distribution by country and cluster of five variables.

Country	Group 1	Group 2	Group 3	Group 4	Total
Argentina	7	8			15
Brazil	2	3	9	28	42
Chili		6	6	7	19
Colombia	2	8	3		13
Costa Rica	1	1			2
Cuba		1			1
Ecuador	1	3			4
Mexico	8	9	2		19
Paraguay	1				1
Peru	1	2			3
Puerto Rico		1			1
Uruguay	2	1			3
Venezuela	1	1			2
Total	26	44	20	35	125

Figure 5 presents the dynamic five-variable HJ-Biplot covering the 125 institutions analyzed. The dynamics are observed with a 90% inertia filter to visualize the main movements of the institutions and a 0% inertia filter for the variables. Furthermore, more than 74% of the observed variance is absorbed, ensuring excellent visualization quality.

Direct correlations are observed between all the variables analyzed, except for Academic Reputation and Academic Staff with Doctorates, which are practically independent. This generates a broad debate about how international and regional academics currently view academic reputation, unrelated to the proportion of academics with doctorates in higher education institutions. This could imply the visibility of an HEI's high-impact research, rather than the volume of scientific output, given that the latter two establish low-level direct correlations.

We can also see universities such as Universidad Federal de Santa Catarina, Universidad Nacional Agraria la Molina, Universidad Estadual de Maringá, The Federal University of Lavras and the Federal University of Pelotas are the most dynamic institutions that continue to be visualized using the inertia filter, which defines them as HEIs with high variability over the analysis period. Increases are observed in the variable of academic staff with doctorates in 2025, but considerable decreases in all the analysis variables by 2024.

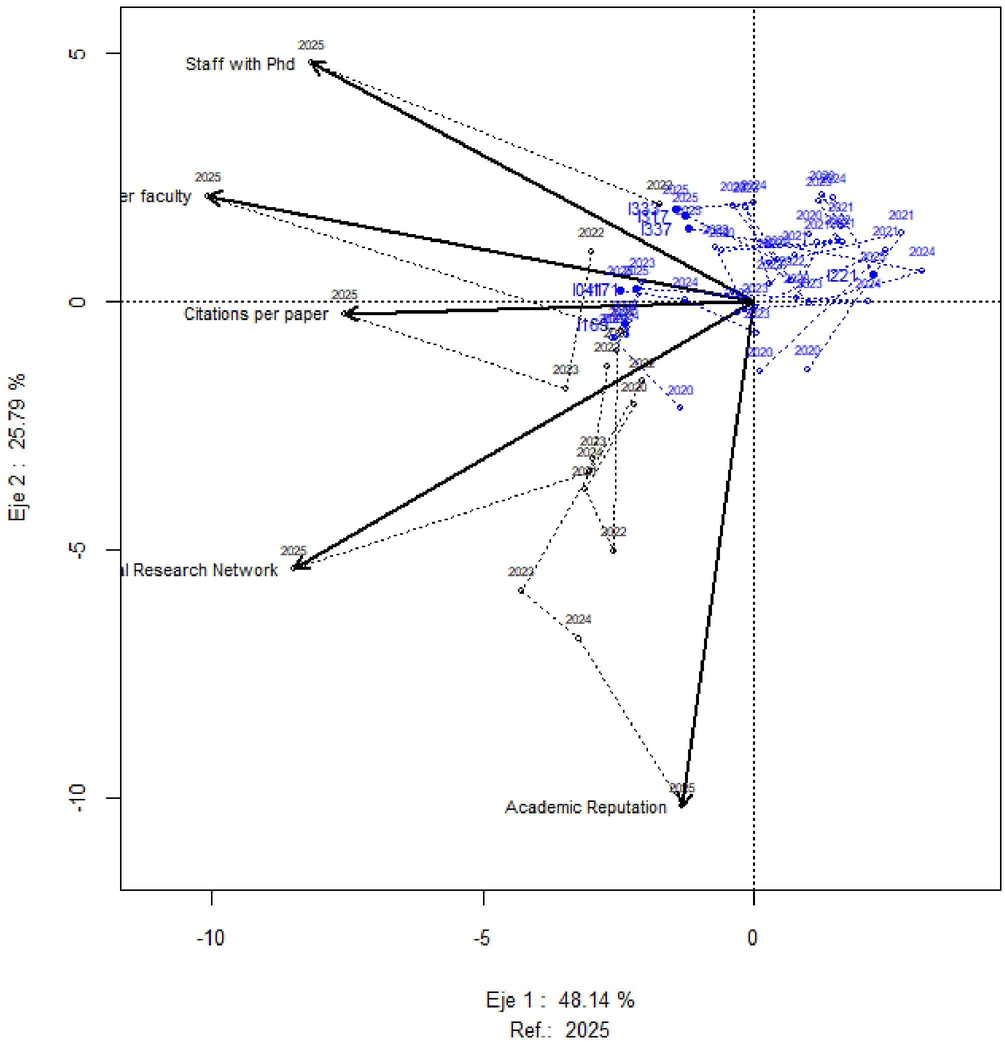

Figure 5. General HJ-Biplot analysis with five variables.

Figure 6 presents the multivariate representation of the HJ-Biplot by cluster analysis. Variance absorptions exceeding 60% are obtained in all groups, indicating acceptable representation quality.

In clusters 1 and 2, a high degree of heterogeneity was detected in the distribution of the groups in relation to the variables analyzed. Likewise, there is a strong correlation between the volume of scientific publications produced by the institutions' academic staff and the proportion of individuals holding doctoral degrees. A strong correlation was also found between the international research network and academic reputation, which, according to the analyses presented, would indicate a strong influence between them. Finally, there is virtually no correlation between publication citations and the other variables analyzed in the aforementioned clusters.

Cluster 3 is the most homogeneous and contains the highest-ranked institutions. Therefore, it is the group with the highest performance, supported by the correlation established by these institutions among all the research-related analysis variables. In this group, once again, Adolfo Ibáñez University, this time accompanied by the National Autonomous University of Mexico, appears as an extreme group, with values well below average, particularly in the case of the second institution, specifically in the scientific productivity indicators.

Finally, the fourth cluster is seen as a highly heterogeneous group and the only one in which the proportion of academics with doctorates shows a strong inverse correlation with faculty research. This cluster acts as a conglomerate without a clear categorization, but its set of variables presents similar results.

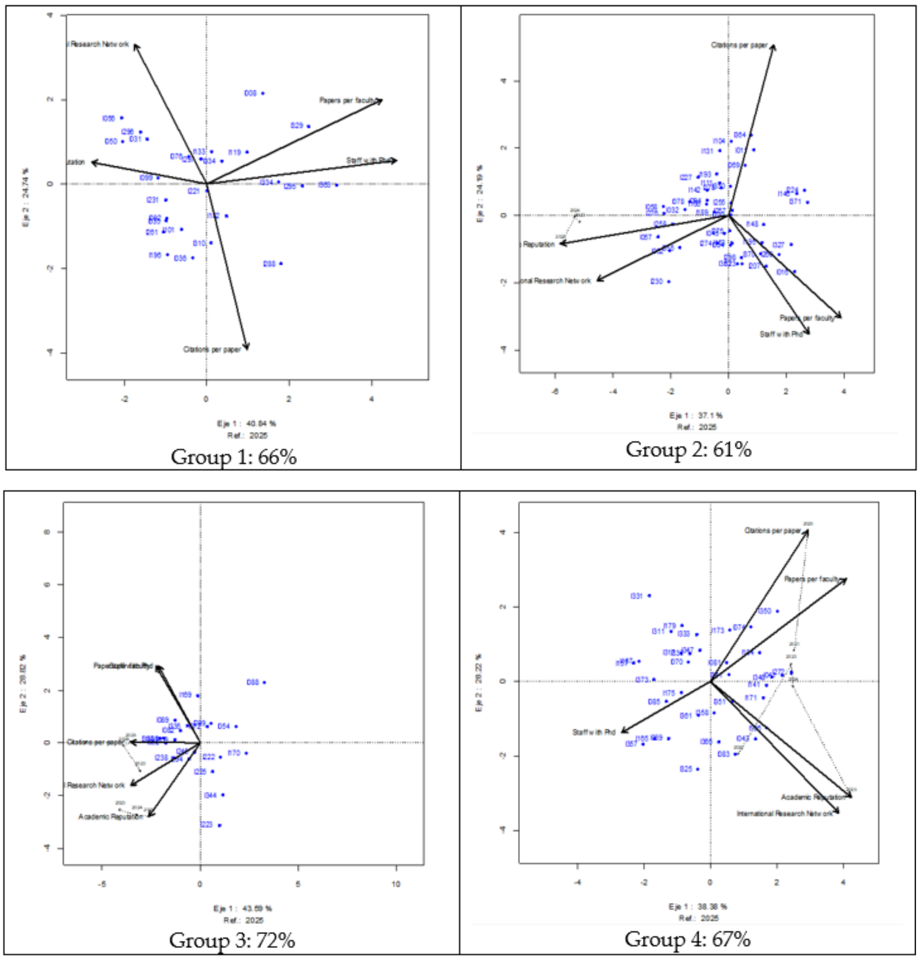

Figure 6. HJ Biplot by cluster, reference 2025.

3.2. Neutrosophic Analysis of University Rankings Using Plithogenic Statistics

To complement the dynamic multivariate analysis of research trajectories in Latin American universities, we employ Plithogenic Statistics, a neutrosophic approach that models the truth (T), indeterminacy (I) and falsity (F) of ranking indicators, capturing the ambiguities and contradictions inherent in university performance [18, 19]. This approach is particularly relevant in the Latin American context, where structural gaps and institutional heterogeneity generate uncertainty in the evaluation of indicators such as publications per professor, citations per article, academic reputation, international research networks and proportion of staff with doctorates.

3.2.1. Application to Segmentation Results

Plithogenic analysis was applied to the clusters identified in the 4-variable (137 institutions) and 5-variable (125 institutions) segmentations described in Sections 3.1 and 3.2. Two representative universities per cluster were selected to illustrate the approach, based on their position in the HJ-Biplot and their temporal dynamics. The indicators analyzed are: publications per professor (PP), citations per article (CA), academic reputation (RA), international research networks (IR), and proportion of staff with doctorates (PD, only in the 5-variable segmentation).

Variable Segmentation

For the segmentation of four variables (PP, CA, RA, RI), neutrosophic values were assigned to each indicator based on normalized ranking data (scale [0, 1]) and expert opinion. For example, for the University of São Paulo (USP) (Cluster 4, leading institution) and the University of Havana (UH) (Cluster 1, with high variability), the following plithogenic values were defined for 2025:

USP (Cluster 4):

- PP: $(T = 0.90, I = 0.05, F = 0.05)$– High number of publications, low uncertainty.
- CA: $(T = 0.85, I = 0.10, F = 0.05)$ – High impact, some interannual variability.
- RA: $(T = 0.80, I = 0.15, F = 0.05)$– Strong reputation, but with subjectivity.
- RI: $(T = 0.95, I = 0.03, F = 0.02)$ – Extensive international networks.

UH (Cluster 1):

- PP: $(T = 0.40, I = 0.50, F = 0.10)$ –Moderate production, high indeterminacy.
- CA: $(T = 0.35, I = 0.55, F = 0.10)$– Low impact, high uncertainty.
- RA: $(T = 0.50, I = 0.40, F = 0.10)$ – Moderate, subjective reputation.
- RI: $(T = 0.30, I = 0.60, F = 0.10)$ – Limited networks, high indeterminacy.

The average plithogenic probability per cluster was calculated using Equation 1. For Cluster 4 (n=35):

$$\boldsymbol{PCl\acute{u}ster\ 4} = \left(\boldsymbol{\Sigma}\frac{\boldsymbol{Ti}}{\boldsymbol{35}}, \boldsymbol{\Sigma}\frac{\boldsymbol{Ii}}{\boldsymbol{35}}, \boldsymbol{\Sigma}\frac{\boldsymbol{Fi}}{\boldsymbol{35}}\right)$$

Assuming estimated average values for the cluster (based on USP and other leading institutions):

- $PP: PPP = (0.85, 0.10, 0.05)$

- $CA: PCA = (0.80, 0.15, 0.05)$
- $RA: PRA = (0.75, 0.20, 0.05)$
- $RI: PRI = (0.90, 0.08, 0.02)$

To combine indicators, the neutrosophic summation was used (Section 2.3):

$$(\boldsymbol{A}_1, \boldsymbol{I}_1) + (\boldsymbol{A}_2, \boldsymbol{I}_2) = (\boldsymbol{A}_1 + \boldsymbol{A}_2 - \boldsymbol{A}_1\boldsymbol{A}_2, \boldsymbol{I}_1\boldsymbol{I}_2)$$

For example, for PP and CA in Cluster 4:

- $TPP + CA = 0.85 + 0.80 - 0.85 \times 0.80 = 0.97$
- $IPP + CA = 0.10 \times 0.15 = 0.015$
- $FPP + CA = 0.05 \times 0.05 = 0.0025$

Result: $\boldsymbol{PPP + CA = (0.97, 0.015, 0.0025)}$, indicating high performance combined with minimal indeterminacy.

The degree of contradiction between RA and RI, based on the high correlation observed in Cluster 4 (Section 3.1), is:

$$\boldsymbol{c(RA, RI) = 1 - 0.85 = 0.15}$$

This reflects a low contradiction, consistent with the homogeneity of Cluster 4.

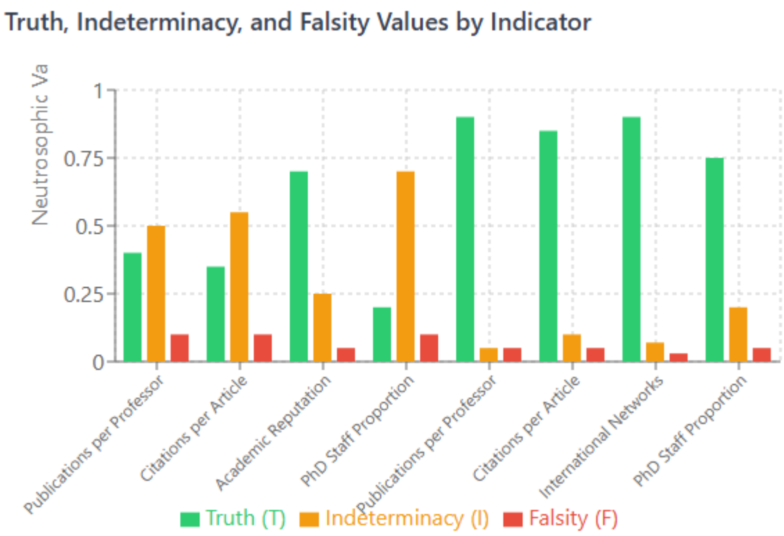

Figure 7: Neutrosophic Analysis of Latin American University Rankings

Variable Segmentation

For the segmentation of five variables (PP, CA, RA, RI, PD), the proportion of staff with doctorates was included. The Adolfo Ibáñez University (UAI) (Cluster 3, atypical) and the Federal University of Santa Catarina (UFSC) (Cluster 4, dynamic) were analyzed. Estimated plithogenic values for 2025:

UAI (Cluster 3):

- PP: $(T = 0.30, I = 0.60, F = 0.10)$– Low productivity, high indeterminacy.
- CA: $(T = 0.25, I = 0.65, F = 0.10)$ –Low impact, high uncertainty.
- RA: $(T = 0.70, I = 0.25, F = 0.05)$– Good reputation, somewhat subjective.
- RI: $(T = 0.40, I = 0.50, F = 0.10)$ – Moderate networks.
- PD: $(T = 0.20, I = 0.70, F = 0.10)$– Low proportion of doctorates.

UFSC (Cluster 4):

- PP: $(T = 0.88, I = 0.08, F = 0.04)$ – High productivity.
- CA: $(T = 0.85, I = 0.10, F = 0.05)$– High impact.
- RA: $(T = 0.78, I = 0.15, F = 0.07)$– Strong reputation.
- RI: $(T = 0.90, I = 0.07, F = 0.03)$ –Extensive networks.
- PD: $(T = 0.75, I = 0.20, F = 0.05)$– High proportion of doctorates.

For Cluster 3 (n=20), the average plithogenic probability is:

- $PP: PPP = (0.35, 0.55, 0.10)$
- $CA: PCA = (0.30, 0.60, 0.10)$
- $RA: PRA = (0.65, 0.30, 0.05)$
- $RI: PRI = (0.45, 0.45, 0.10)$
- $PD: PPD = (0.25, 0.65, 0.10)$

The contradiction between RA and PD, based on the null correlation (Section 3.2), is:

$$\boldsymbol{c(RA, PD) = 1 - 0.05 = 0.95}$$

This confirms the high contradiction observed in the HJ- Biplot, where reputation does not align with the proportion of PhDs.

Table 6: Plithogenic Values by Cluster and Variable

Cluster	Variable	Representative University	Truth (T)	Indeterminacy (I)	Falsehood (F)	Interpretation
1	PP	University of Havana	0.40	0.50	0.10	Moderate production, high uncertainty
1	AC	University of Havana	0.35	0.55	0.10	Low impact, high indeterminacy
3	RA	Adolfo Ibáñez University	0.70	0.25	0.05	Good reputation, somewhat subjective

Cluster	Variable	Representative University	Truth (T)	Indeterminacy (I)	Falsehood (F)	Interpretation
3	P.S.	Adolfo Ibáñez University	0.20	0.70	0.10	Low proportion of doctorates
4	PP	University of São Paulo	0.90	0.05	0.05	High number of publications
4	AC	University of São Paulo	0.85	0.10	0.05	High scientific impact
4	RI	UFSC	0.90	0.07	0.03	Extensive international networks
4	P.S.	UFSC	0.75	0.20	0.05	High proportion of doctorates

Note: PP = Publications per Professor, CA = Citations per Article, RA = Academic Reputation, RI = International Networks, PD = Proportion of Staff with PhDs

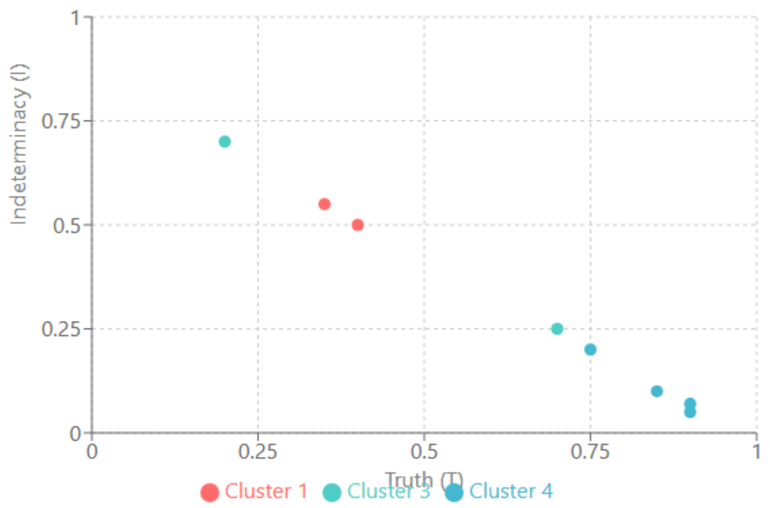

Figure 8: Truth vs Indeterminacy Distribution by Cluster

3.2.2. Contributions to Research Paths

The plithogenic analysis reveals that high-performance clusters (3 and 4) present high truth values (T>0.75) and low indeterminacy (I<0.20) in indicators such as PP, CA, and RI, reflecting consolidated research trajectories. In contrast, clusters 1 and 2 show high indeterminacy (I>0.50), indicating structural challenges in scientific production and visibility.

The inclusion of PD in the 5-variable segmentation accentuates the gaps, with universities such as UAI showing high indeterminacy in PD (I=0.70), suggesting that their reputation is not backed by formal research capacity.

These results enrich multivariate analysis by quantifying uncertainty and inconsistencies, offering a tool for universities to identify specific areas for improvement. For example, policies that reduce indeterminacy in PhD (through doctoral training) could improve performance in lower-performing clusters. Plithogenic Statistics, by modeling these dynamics, contributes to a more complete understanding of research trajectories, aligning with the article's title and supporting Latin America's academic competitiveness on the global stage.

4. Applications

The results of this study, which combine dynamic multivariate analysis with Plithogenic Statistics, offer a strategic tool for Latin American universities to boost their continuous improvement processes in research. The identification of differentiated clusters based on research performance, enriched by the plithogenic approach, allows institutions to position themselves in more realistic reference groups, considering not only performance on indicators such as publications per professor, citations per article, academic reputation, and international research networks, but also the uncertainties and contradictions associated with these indicators. For example, the plithogenic analysis shows that universities in clusters 1 and 2 face high uncertainty in indicators such as publications per professor and citations per article, reflecting structural limitations in their research trajectories. In contrast, clusters 3 and 4, dominated by Brazilian and Chilean universities, present solid performance with low uncertainty in these same indicators, indicating more consolidated research trajectories. This approach, which incorporates uncertainty, allows universities such as the University of Havana, in Cluster 1, to identify the need to strengthen their scientific production to reduce the ambiguity in their positioning, while institutions such as the Federal University of Santa Catarina, in Cluster 4, can consolidate their leadership. These distinctions can be integrated into university strategic plans to prioritize investments in scientific productivity, internationalization, and the training of doctoral scholars, tailored to the specific needs of each cluster.

From a public policy perspective, the results provide national higher education organizations and quality assurance agencies with a framework for designing more precise support instruments. The plithogenic analysis highlights significant structural gaps, such as the marked contradiction between academic reputation and the proportion of staff with doctorates in Cluster 3, where universities such as Adolfo Ibáñez University show high uncertainty in the latter indicator. This suggests that public policies should go beyond promoting the number of publications, also focusing on strengthening internal academic capacities by training doctoral graduates and consolidating international research networks. For example, universities with high uncertainty in the proportion of staff with doctorates could benefit from national programs that incentivize doctoral training, thereby reducing ambiguities in their performance. This combined framework of multivariate and plithogenic analysis is replicable for long-term monitoring of the impact of scientific promotion policies, offering a more complete view of how interventions affect research trajectories in the region.

Finally, the dynamic HJ- Biplot approach , complemented by Plithogenic Statistics, represents a powerful tool for internal university quality management. This methodology allows institutions not only to evaluate their static performance in the rankings but also to understand the evolution of their research indicators over time, considering the uncertainties and contradictions that influence their positioning. For example, Adolfo Ibáñez University, with high uncertainty in scientific productivity indicators, can use this analysis to identify critical areas for improvement, such as strengthening its research capacity, while the Federal University of Santa Catarina, with robust performance and low uncertainty, can consolidate its position in international networks and doctoral training. In a context of increasing international competition, this combined approach provides Latin American universities with a comparative advantage, allowing them to make decisions based on a deeper understanding of the dynamics of their research trajectories and strengthen their position in the global higher education market.

5. Conclusions

This study demonstrated that the research trajectories of Latin American universities present heterogeneous evolution patterns, influenced by structural gaps in scientific productivity, academic impact, and international collaboration networks. Through hierarchical cluster analysis, dynamic HJ-Biplot representations, and Plitogenic Statistics, clusters of institutions with distinct profiles were identified, highlighting high-performing groups dominated by Brazilian and Chilean universities [18, 19]. The incorporation of the plitogenic approach made it possible to capture uncertainties and contradictions among indicators, enriching the understanding of these trajectories.

The results show that indicators such as publications per professor and citations per article maintain strong correlations in the best-positioned institutions, especially in Clusters 3 and 4, where they exhibit solid performance with low uncertainty. However, academic reputation does not always align with the proportion of academics with doctoral degrees, evidencing a notable contradiction, particularly in Cluster 3, where universities such as Adolfo Ibáñez University exhibit high uncertainty in indicators of scientific productivity and doctoral training. This tension between perception and actual research capacity highlights the importance of considering uncertainty in the evaluation of university performance. The temporal stability of some universities contrasts with the high variability of others, such as the University of Havana in Cluster 1, which shows great uncertainty in publications and citations, reflecting dynamics of institutional consolidation or vulnerability in the global context.

The four-variable analysis identified clusters focused on academic production and visibility, while incorporating the proportion of staff with doctorates into the five-variable analysis revealed deeper structural gaps related to institutional training. High-performing clusters include universities with a consolidated research tradition, such as the Federal University of Santa Catarina, which shows low uncertainty in key indicators. In contrast, lower-performing clusters, such as Clusters 1 and 2, face limitations in scientific production and academic staff qualifications, with high uncertainty that hinders their positioning in international rankings.

In the Latin American context, the findings underscore the strong asymmetries between countries and institutions. Brazil and Chile concentrate the majority of universities in leading clusters, while other nations face significant challenges in achieving international research standards. The proportion of staff with doctorates accentuated these differences, showing that consolidating highly qualified academic bodies remains a challenge in the region. The plithogenic analysis highlights that the high uncertainty in this indicator, especially in universities in lower-performing clusters, requires specific attention to improve research trajectories. Therefore, the study reaffirms the importance of developing differentiated public policies that promote research training and the strengthening of international networks, integrating the plithogenic perspective to address ambiguities and contradictions in ranking indicators, in order to boost Latin America's academic competitiveness on the global stage.

Finally, dynamic multivariate methods, such as HJ- Biplot, combined with Plithogenic Statistics, are consolidated as robust tools for longitudinal monitoring of research quality. This combined approach provides key information for strategic decision-making in Latin American higher education, allowing universities and governments to design strategies that not only improve ranking performance but also reduce uncertainty in critical indicators, strengthening the region's research trajectories and global position.

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