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Innovation Ecosystems and Economic Performance in Latin America: A Multivariate and Plithogenic Neutrosophic Approach to the Global Innovation Index

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Abstract. The article is a retrospective assessment of the innovation landscape in Latin America between 2012-2022. The assessment is conducted through a multivariate and neutrosophic plithogenic approach based on the Global Innovation Index (GII). The Principal Components Analysis (PCA) assesses the factors constituting the GII creation to reveal invisible dimensions of innovation, while k-means clustering divides the observations into three clusters relevant to structural ability and innovative achievements. Moreover, a multiple linear regression calculates the relative importance of the GII pillars compared to the mean value, revealing that the economic dimension of resources/infrastructure, human capital, and research generate the highest results. ANOVA and contingency tables analyze the innovative spheres and their corresponding relationships to economic/development levels. The longitudinal analysis reveals a general stagnation of innovation in Latin America. However, countries are straying on different paths. The analysis strengthens through the neutrosophic plithogenic evaluation from experts' feedback of contentment within each IGI pillar. The Iadov Neutrosophic Plithogenic approach shows high degrees of indeterminacy in poorly performing countries which indicates that differentiated policies are suggested. Therefore, the results based on IGI 2024 [5] and neutrosophic plithogenic assessment suggest that public policies should be differentiated but not at the expense of what fosters simultaneous innovation/transfer and structural abilities since Latin America is heterogeneous.

Keywords: Innovation; Latin America; Global Innovation Index; multivariate analysis; innovation clusters; multiple linear regression; development gaps; time course; neutrosophic plitogenicity; plitogenic Iadov.

1. Introduction

Innovation has been consolidated in recent decades as a central element for economic growth and international competitiveness, competitiveness, and human development [1]. Since the second half of the 20th century, endogenous growth models have highlighted that a nation's innovation capacity is a key determinant of its long-term prosperity [2]. Today, in a context of accelerated technological transformations, geopolitical tensions and environmental crises, innovation is considered not only a lever of productivity, but also an essential tool for achieving the Sustainable Development Goals [3].

The Global Innovation Index (GII), developed by WIPO, Cornell University and INSEAD, has become the leading international benchmark for measuring countries' innovation capabilities through input (institutions, infrastructure, human capital) and output (knowledge production, creative goods and services) indicators [4]. However, recent reports warn that, after an initial surge due to the COVID-19 pandemic, global investments in innovation have declined, exacerbating regional inequalities in innovation capacity [5].

To address these inequalities in Latin America, this study combines a multivariate approach with a neutrosophic plithogenic analysis based on the Iadov Neutrosophic Plithogenic method. While multivariate analysis, including techniques such as Principal Component Analysis (PCA), k-means clustering, and multiple linear regression, allows for the identification of quantitative patterns in innovation ecosystems, the neutrosophic plithogenic approach assesses stakeholders' perceptions of satisfaction with the pillars of the IGI, modeling uncertainty and contradictions inherent in the region's heterogeneous contexts. This integrated approach, detailed in section 5, complements the quantitative findings by revealing how subjective perceptions reinforce the identified structural and economic gaps, offering a more comprehensive perspective for designing differentiated public policies that strengthen innovation ecosystems in Latin America.

1.1 Innovation in Latin America: structural challenges.

Latin America faces particular challenges in terms of innovation. Historically, the region have had R&D investment levels below 1% of GDP, considerably below the OECD average [6]. Dependence on extractive sectors, weak higher education and research systems, and limitations in technological infrastructure contribute to the innovation gap between Latin America and advanced economies.

Several studies have identified that the region presents "incomplete innovation ecosystems", characterized by the lack of articulation between universities, governments, and companies [7]. In addition, the market sophistication index and the quality of institutions, two critical pillars for innovation, tend to show low performance in most Latin American countries [8].

The GII 2024 reinforces these observations, noting that despite individual success stories, the region has shown stagnation in recent years, with no apparent convergence towards the innovation levels of other emerging areas such as Asia [5].

1.2 Reference framework on innovation

The theory of technological capabilities holds that innovation is not to spontaneous product, but the cumulative result of investments in infrastructure, education, research, and collaborative networks [9]. From this perspective, countries that build robust structural capabilities can translate them into sustainable innovative results.

Among the variables considered fundamental for the analysis of innovation ecosystems are:

- Institutions: A measure of the quality of the legal framework and the efficiency of governments in promoting innovation, fundamental for reducing uncertainties in the business environment [10].
- Human Capital and Research: Includes indicators of higher education, professional training, and investment in R&D, which are the basis for knowledge generation [11].
- Infrastructure: reflects the degree of development in information and communication technologies (ICTs), logistics, and energy necessary to support innovative activities [12].
- Market Sophistication: Considers access to credit, investor protection, and market competition, factors that facilitate the allocation of resources to innovative projects [13].
- Business Sophistication: Represents the capacity of companies to innovate, including private R&D investment, and the presence of industrial clusters [14].
- Knowledge and Technology Production: Refers to the number of patents, scientific publications, and high-tech exports [15].
- Creative Outcomes: Related to cultural industries, creative goods, and new technologies in consumer products [16].

On the other hand, external economic variables used as measures of structural context include Gross National Income (GNI) per capita, Gross Domestic Product (GDP) per capita adjusted for purchasing power parity, and the categorical level of income according to the World Bank classification [8].

However, recent studies indicate that the relationship between capabilities and practical innovation is mediated by contextual factors, such as governance, access to financing, and the knowledge absorption capacity of companies [17]. Therefore, innovation analysis requires multivariate approaches that capture the complexity of these interactions.

1.3 Rationale for the research

Despite the abundant literature on the determinants of innovation, there is a gap in studies that integrate multivariate, longitudinal, and regional approaches to analyze the dynamics of innovation in Latin America. Most research focuses on cross-sections or individual case studies.

In this work, we address this limitation through a principal component analysis (PCA) applied to GII indicators, followed by k-means clustering of country-year observations (2012-2022), and their subsequent association with economic indicators such as GNI per capita and GDP PPP.

This approach seeks to identify differentiated patterns of innovation in the region and analyze how these relate to levels of economic development, contributing to to more precise understanding of the challenges and opportunities for strengthening innovation ecosystems in Latin America.

2. Materials and Methods

This study employs a quantitative, non-experimental, retrospective longitudinal approach to analyze country-year innovation patterns in Latin America from 2012 to 2022. Multivariate statistical methods were used to identify latent innovation structures, shape homogeneous clusters of observations, and assess their relationship with structural economic indicators.

The applied methodology integrates data reduction techniques, cluster analysis, tests of association, and comparison of means, making it possible to characterize the innovative profiles emerging in the region and explain their links with the socio-economic context. The analysis strategies used, the variables considered, and the interpretation criteria adopted are described below.

2.1. Details of the used methods

Type and design of research: The present study is framed within quantitative research, a non-experimental approach, and an exploratory-correlational design. Since country-year observations from 2012 to 2022, extracted from the Global Innovation Index (GII), were analyzed, a retrospective longitudinal design of short time series was adopted.

The research sought to explore multivariate patterns of innovation in Latin America and their association with structural economic variables, without manipulating the conditions of the study subjects.

Level of research: The research was explanatory since it sought not only to describe the differences between the shaped clusters but also to explain the relationships between innovative capabilities, innovation performance, and levels of economic development in the Latin American context, following the criteria of [24].

Population and sample: The unit of analysis was the country-year observations registered in the Global Innovation Index for Latin American countries between 2012 and 2022, considering all the observations available continuously across that period.

We worked with 209 valid observations, representing multiple annual records from the same countries.
The variables used were:

- Innovation variables (independent variables for PCA and clustering): Institutions.
- Human Capital and Research. Infrastructure.
- Market sophistication. Business sophistication.
- Knowledge production and technology. Creative results.
- External economic variables (associated variables for further analysis): Gross National Income (GNI) per capita (current US dollars). Gross Domestic Product (GDP) per capita, purchasing power parity. Categorical income level (low, medium, high, medium -high, high).

2.2. Statistical methods used

Multiple linear regressions: To identify the impact of the Global Innovation Index's pillars on the total country-year innovation score, the assumptions of normality, homoscedasticity, and absence of multicollinearity were verified before estimating the model. The analysis made it possible to assess the relative contribution of each dimension to the overall innovative performance of the countries analyzed, thus complementing the multivariate understanding of the phenomenon studied [18, 21].

Principal Component Analysis (PCA): PCA was applied to reduce the dimensionality among the innovation variables, ensuring adequacy through the Kaiser-Meyer- Olkin test (KMO = 0.763) and Bartlett's test of sphericity ($p<0.001$). The criterion of eigenvalues greater than one (Kaiser, 1960) was used to retain two principal components, and subsequently, a Varimax orthogonal rotation was applied to clarify the interpretation of the factors [21].

k-means cluster analysis: With the PCA factor scores, a cluster analysis was performed using the k-means clustering algorithm, setting the formation of three clusters based on conceptual and exploratory differentiation. Cluster membership allowed the country-year observations to be profiled according to their patterns of structural innovation and outcomes.

Analysis of Variance (ANOVA): To evaluate economic differences between clusters, one-factor analysis of variance was performed, comparing GNI and GDP per capita levels. Given the detection of heterogeneity of variances using Levene's test, post-hoc comparisons were applied using the Games-Howell method, which is suitable for unequal variances [18].

Contingency Tables and Chi-square test: Associations between the number of clusters and the categorical income level were analyzed using contingency tables and Pearson's Chi-square test. Based on the procedures described by Agresti [19], the linear trend between income level and innovation pattern was also evaluated.

Analysis of Temporal Evolution: Finally, the evolution of the Global Index scores in Latin America between 2012 and 2022 was analyzed, identifying trends of stagnation, regression, or consolidation of innovation gaps at the regional level.

2.3. Criteria for interpretation of results

A significance level of $p<0.05$ was considered for all statistical tests. Effect sizes were evaluated by eta squared in ANOVA analyses, considering the interpretation criteria of Muller [20]: 0.01 (small), 0.06 (medium), 0.14 (large). The clusters were interpreted conceptually from the factorial centroids, and scatter plots and mean plots were used as visual support to validate the separation and characteristics of the groups.

2.4. Plithogenic analysis: IADOV method.

Mathematical modeling, from neutrosophic logic to plithogenic logic, is a methodology that focuses on incorporating indeterminacy and contradiction into the evaluation of sets and systems. Plithogenic logic has the following characteristics:

1. Neutrosophic sets: These sets allow quantifying indeterminacy (I) through a third parameter, in addition to true membership (T) and false membership (F). The values of T, I and F are independent and their total sum is between 0 and 3 [25,31, 33] .
2. Membership functions: Within a universe of discourse U, a Neutrosophic Set (NS) is defined by three functions : $u_A(x), r_A(x), v_A(x) : X \rightarrow \,]0-, 1+[$; that satisfy the condition $0 \leq -\inf u_A(x) + \inf r_A(x) + \inf v_A(x) \leq \sup u_A(x) + \sup r_A(x) + \sup v_A(x) \leq 3+$ for all $x \in X$. $u_A(x), r_A(x), v_A(x)$are the truth, indeterminacy and falsity membership functions of x in A, respectively, and their images are standard or non-standard subsets of $]0-, 1+[$.
3. Plithogenic: Represents the creation and evolution of entities from dynamics and fusions of previous entities that may be contradictory, neutral or non-contradictory [26, 27] . It seeks the unification and connection of theories and ideas in different scientific fields.
4. Plithogenic: an extension of the classical, fuzzy, intuitionistic, and neutrosophic sets. A plithogenic set (P, a, V, d, c) :
   a) Where "P" is a set, "a" is an attribute (usually multidimensional), "V" is the range of attribute values, "d" is the degree of membership of the attribute value of each element x to the set P for some given criteria (x ∈ P), and "d" stands for " d_F", or " d_{IF} ", or " d_N", when it is a fuzzy degree of membership, an intuitionistic fuzzy membership or a neutrosophic degree of membership, respectively, of an element x to the plithogenic set P;
   b) "c" means " c_F", or " c_{IF}", or " c_N", when it is a fuzzy attribute-value contradiction degree function, intuitionistic fuzzy attribute-value contradiction function, or neutrosophic attribute-value contradiction function, respectively.
   c) The functions are defined according to the applications that the experts need to solve. $d(\cdot,\cdot)$and $c(\cdot,\cdot)$then, the following notation is used: $x(d(x,V))$where $d(x, V) = \{d(x, v), \text{for all } v \in V\}, \forall x \in P$. The attribute value contradiction function is calculated between each attribute value with respect to the dominant attribute value (denoted by) in particular, and also for other attribute values v_D.

1. Plithogenic: These include union (OR), intersection (AND), and other aggregation operators that combine attribute values based on t_{norm} and t_{conorm}. Linear and nonlinear aggregation operations can be created.
2. Contradiction and Aggregation Calculation: The contradiction function c evaluates the contradiction between attribute values. Therefore, they influence how t_{norm} and $t_{conorm}$when applied to create aggregation operators.
3. If t_{norm} is applied to the value of the dominant attribute indicated by v_D, and the contradiction between $v_D$and $v_2$is $c(v_D, v_2)$, then it is applied to the attribute value $v_2$as follows:

$$[1 - c(v_D, v_2)] \cdot t_{norm}(v_D, v_2) + c(v_D, v_2) \cdot t_{conorm}(v_D, v_2), \tag{1}$$

4. Or according to the following symbology:

$$[1 - c(v_D, v_2)] \cdot (v_D \wedge_F v_2) + c(v_D, v_2) \cdot (v_D \vee_F v_2), \tag{2}$$

5. Similarly, if $t_{conorm}$is applied to the value of the dominant attribute denoted by v_D, and the contradiction between $v_D$andv_2 is $c(v_D, v_2)$, then it is applied to the value of the attribute v_2:

$$[1 - c(v_D, v_2)] \cdot t_{conorm}(v_D, v_2) + c(v_D, v_2) \cdot t_{norm}(v_D, v_2), \quad (3)$$

6. Or, according to the following symbology:

$$[1 - c(v_D, v_2)] \cdot (v_D \vee_F v_2) + c(v_D, v_2) \cdot (v_D \wedge_F v_2), \quad (4)$$

7. Plithogenic neutrosophic intersection and union: They are defined in such a way that one criterion is applied for membership and its opposite for non-membership, while for indeterminacy the average is taken.
8. plithogenic is defined as:

$$(a_1, a_2, a_3) \wedge_P (b_1, b_2, b_3) = \left(a_1 \wedge_F b_1, \frac{1}{2}[(a_2 \wedge_F b_2) + (a_2 \vee_F b_2)], a_3 \vee_F b_3\right) \quad (5)$$

9. plithogenic is defined as:

$$(a_1, a_2, a_3) \vee_P (b_1, b_2, b_3) = \left(a_1 \vee_F b_1, \frac{1}{2}[(a_2 \wedge_F b_2) + (a_2 \vee_F b_2)], a_3 \wedge_F b_3\right), \quad (6)$$

10. Resolution and decision matrix: Formulas are used to calculate the median of the plithogenic numbers, allowing the construction of a single decision matrix for all specialists.

$$\text{median}_{i=1}^{m}\{PN_i\} = (\text{median}_{i=1}^{m}\{T(PN_i)\}, \text{median}_{i=1}^{m}\{I(PN_i)\}, \text{median}_{i=1}^{m}\{F(PN_i)\}),$$

Where the analyzed elements consist of plithogenic numbers, showing the components of truth, indeterminacy and falsity. In other words, it means that the median of a set of plithogenic numbers is defined as the plithogenic number of the medians of its components PN_i, $T(PN_i)$, $I(PN_i)$, and$F(PN_i)$

To compare relationships between quadrants, the following formula is used to blur a neutrosophic number:

$$\mathcal{S}([T, I, F]) = \frac{2 + T - I - F}{3} \quad (8)$$

• For each row of the pairwise comparison matrix, calculate a weighted sum based on the sum of the product of each cell by the priority of each corresponding alternative or criterion (see Table 1).

Table 1: Linguistic expression used to determine the level of importance of the factor on the variable.

Linguistic Expression	Scale	plithogenic (T, I, F)	S
Poor significance (PS)	0	(0,0,9,1)	0.03
Least significant (LS)	1	(0,2,0.8,0.8)	0.20
Low significance (LS)	2	(0.4,0.7,0.6)	0.37

Moderately significant (MS)	3	(0.5,0.5,0.5)	0.50
Significant (S)	4	(0.6,0.3,0.4)	0.63
Most significant (MS)	5	(0.8,0.2,0.2)	0.80
Very significant (VS)	6	(0.9,0,0.5)	0.95

The Plitogenic IADOV technique is an assessment method that uses five questions, three multiple-choice and two open-ended, to measure respondent satisfaction [25,31] . The peculiarity of this method lies in its "IADOV Logical Grid", which connects three of the questions in a way that is hidden from the participant in order to infer satisfaction through their interrelationships. By extending this technique to the plitogenic context and using a neutrosophic scale [27,28] , the ability to measure indeterminate or inaccessible aspects with conventional methods is introduced. This makes it possible to address the complexity of respondents' perceptions. It requires an assessment system adapted to the neutrosophic model to accurately capture expert opinions (see Table 2). This system and its neutrosophic equivalents are defined as the scoring function A of a neutrosophic number as proposed by Basset [29, 30] .

Table 2: Expert evaluation system.

Linguistic term	SVNN	Scale
Clearly satisfied	(1,0,0)	0.50
More satisfied than dissatisfied	(0.75,0.20,0.25)	0.40
Indeterminacy	I	0.25
More dissatisfied than satisfied	(0.25,0.70,0.75)	0.15
Clearly dissatisfied	(0,0,1)	0.00
Contradictory	(1,0,1)	1.00

The term I in Neutrosophic is interpreted as a unit of indeterminacy . Another component of the method is the IADOV Logic Table, which assigns numerical values to three closed-ended questions applied to experts (based on the references consulted) . If necessary, open-ended questions can also be applied to the surveys . Among the questions used in this study to assess perceptions about the pillars of the Global Innovation Index (GII) were:

1. Do you think that the **institutions** in your country adequately promote innovation and economic development?
2. What **areas of human capital and research** require urgent attention to strengthen innovation ecosystems in your region?
3. What are the **most significant advances** you've observed in your country's innovation **infrastructure** in recent years?
4. Can you describe any specific experiences where you felt that **market sophistication** or **business sophistication** was key to the success of innovative projects?
5. Are you satisfied with the way **knowledge and technology are produced , and creative outcomes** are generated, in your community/country's innovation ecosystem?

To calculate the Neutrosophic Plithogenic Global Satisfaction Index (NPGSI) of the respondentsH_N^P, the aggregation operator was used, considering the evaluations of each element X to the plithogenic set P ; x ∈ Pd_F d_{IF} d_N. Thus, the NPGSI is obtained as the sum of the elements analyzed within the plithogenic subset (S_i^P) evaluated [34, 35].

$$H_N^P\left(S_{1,}^P S_2^P, \ldots, S_n^P\right) = \sum_{i=1}^{n} \left[w_j\, , S_i^P\right] \tag{11}$$

3. Results

The main results obtained from the analysis are presented below. These findings allow us to characterize innovation patterns in Latin America from 2012 to 2022 and explore their relationship with the countries' levels of economic development in the region.

The analysis of the temporal evolution of the Global Innovation Index in Latin America from 2012 to 2022 shows relevant dynamics both at the regional level and at the level of specific countries. First, it is observed that, through the decade, most countries experienced a general stagnation or slight decline in their innovation scores. This pattern reflects, in part, the region's structural difficulties in consolidating sustained processes to strengthen its innovative ecosystems.

Chile, Costa Rica, and Mexico consistently stand out as the countries with the highest levels of relative innovation in the Latin American context, maintaining higher positions compared to the rest of the region in most of the years analyzed. However, even these countries show oscillations, particularly as of 2018, with a downward trend in their indicators.

At the opposite extreme, countries such as Honduras, Nicaragua, and Guatemala have the lowest scores in the series, showing relatively flat or declining trajectories, suggesting persistent structural limitations in developing innovative capabilities. Particularly notable is the evolution of countries such as Peru and Ecuador, which, although starting from intermediate positions in 2012, experienced a sustained decline in their scores in recent years, especially as of 2020, coinciding with the economic and social impact of the COVID-19 pandemic.

Figure 1 also reveals that, although there are annual fluctuations, there is no significant convergence between countries; On the contrary, there is a relatively stable dispersion, with the leading and lagging countries maintaining their relative positions, thus consolidating the regional innovation gaps.

Finally, it should be noted that, in general, the Latin American region has not shown a consistent trend towards the sustained improvement of its innovation systems in the last decade, posing critical challenges for public policies to strengthen scientific, technological, and entrepreneurial capabilities.

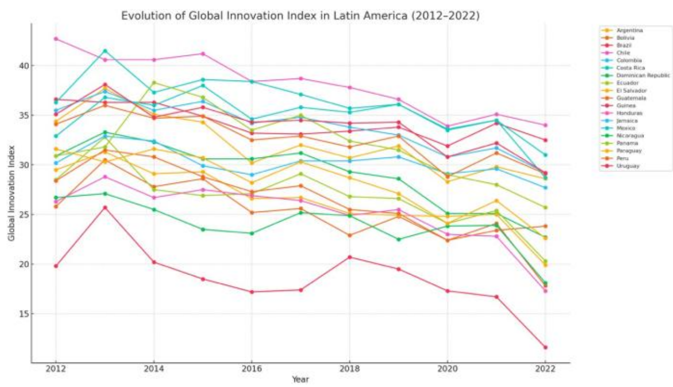

Figure 1. Time evolution of the Global Innovation Index.

3.1 Linear regression

A multiple linear regression model was estimated to evaluate the contribution of the different pillars of the Global Innovation Index to the total country-year innovation score. The model presented a good overall fit (adjusted R2), indicating that the variables considered explained a considerable proportion of the variability in innovation performance. Among the factors analyzed, infrastructure, human capital and research, and business sophistication showed weaker or non-significant associations.

The constant value represents the Global Innovation Index score when all the innovation pillars are zero; the non-significance of this data in practice is irrelevant because these zero values are not realistic in economic or innovation contexts. These results suggest that, in the Latin American context, structural capabilities related to infrastructure and human capital have a particularly relevant weight in countries' innovative positioning.

Table 3. Linear regression results.

Variable	B	Std. Error	Beta	t	Sig. (p-value)	Tolerance	VIF
(Constant)	-0.016	0.016		-0.977	0.330		
Institutions	0.100	0.000	0.184	393.867	0.000	0.622	1.607
Human Capital and Research	0.099	0.000	0.145	261.357	0.000	0.443	2.256
Infrastructure	0.100	0.000	0.162	297.568	0.000	0.460	2.173
Market Sophistication	0.100	0.000	0.143	361.584	0.000	0.873	1.145
Business Sophistication	0.100	0.000	0.105	218.941	0.000	0.598	1.673
Knowledge and Technology Products	0.250	0.000	0.294	527.062	0.000	0.438	2.282
Creative Results	0.250	0.000	0.384	811.764	0.000	0.609	1.642

3.2 Major Component Analysis

Before the application of Principal Component Analysis (PCA) (Table 4), the adequacy of the data was evaluated through two classic tests: the Kaiser-Meyer- Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The KMO value obtained was 0.763, which, according to the classification proposed by Kaiser (1960), indicates to "medium to “good” adequacy to proceed with factor analyses. According to the criteria of Hair et al. (2010), values above 0.7 are considered satisfactory in social science research. Likewise, Bartlett's test was significant ($p < 0.001$), validating that the variables present sufficient correlations to justify a dimension reduction model.
Regarding the communalities, the results show that variables such ace Infrastructure, Knowledge and Technology products, and Business sophistication, present extraction values above 0.7, which reflects an adequate representation in the factor space. In contrast, the variable Market sophistication obtained a low communality (0.183), suggesting that the extracted components do not efficiently explain it and should be critically observed in later stages.
Concerning the variance explained, the PCA allowed us to extract two principal components following the Kaiser criterion, since they have eigenvalues greater than one. The first component explains 47.2% of the total variance, and the second 14.6%, accumulating 61.9% of the original variability between them. This level of explained variance is considered acceptable for studies in social sciences and applied biometrics [19].

Table 4. Principal Component Analysis Results

Analysis	Measure	Value
KMO and Bartlett's Test	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.763
	Bartlett's Test of Sphericity (Approx. Chi-Square)	499.142
		df
		Sig. (p-value)
Communalities	Variable	Initial
	Institutions	1.000
	Human Capital and Research	1.000
	Infrastructure	1.000
	Market Sophistication	1.000
	Business Sophistication	1.000
	Knowledge and Technology Products	1.000
	Creative Results	1.000
Total Variance Explained	Component	Initial Eigenvalues
		Total
	1	3.306
	2	1.025
	3	.891
	4	.728
	5	.452
	6	.336
	7	.262

The analysis of the component matrix (Table 5) reveals that the first factor loads firmly on variables such as Human Capital and Research, Knowledge and Technology products, Creative results, and Infrastructure, indicating a possible structural dimension of innovative capabilities. On the other hand, the second factor shows mixed positive and negative loadings, especially on Infrastructure and Business Sophistication, suggesting a second dimension more associated with market dynamics or differentiation of innovative ecosystems. However, given that the loadings still present sign crossings, performing a Varimax orthogonal rotation are recommended to facilitate a more simple interpretation of the components.

Table 5. PCA Component Matrix.

	Component	
	1	2
Institutions	0.647	0.387
Human Capital and Investigation	0.781	0.120
Infrastructure	0.702	0.598
Market sophistication	0.424	0.059
Business sophistication	0.671	-0.548
Knowledge and Technology products	0.830	-0.166
Creative results	0.683	-0.415

After applying orthogonal Varimax rotation (Table 6), the factor loadings were restructured, significantly clarifying the interpretation of the extracted components. According to the results, the factorial solution maintains two principal components that explain 61.9% of the total variance of the data, an adequate value considered for studies in social sciences and applied biometrics [21].

Table 6. Total difference explained after Varimax .

Component	Initial eigenvalues			Sums of loads squared by extraction			Sums of loads squared by rotation		
	Total	% of difference	% accumulated	Total	% of difference	% accumulated	Total	% of difference	% accumulated
1	3.306	47.232	47.232	3.306	47.232	47.232	2.185	31.214	31.214
2	1.025	14.644	61,876	1.025	14.644	61,876	2.146	30,662	61,876
3	0.891	12,730	74.606						
4	0.728	10.397	85.003						
5	0.452	6.456	91,458						
6	0.336	4.794	96.253						
7	0.262	3.747	100,000						

Regarding individual variance, the first rotated component explains 31.2%, while the second component explains 30.7%. This more balanced distribution in the contribution of each factor is consistent with the purpose of Varimax rotation, which seeks to maximize the interpretability of the components by minimizing cross-loadings [22,23].

The rotated component matrix (Table 7) shows that the first component groups together variables such as Infrastructure, Institutions, and, to a lesser extent, Human Capital and Research, as well as Knowledge and Technology Products. These variables present factor loadings above 0.6, suggesting that this first component can be conceptualized as a dimension of "Structural Innovation capabilities". In the second component, on the other hand, variables such as Business Sophistication, Creative Results, and Knowledge and Technology Products stand out, suggesting the existence of a dimension oriented towards "Sophistication of results and innovative ecosystems".

Table 7. Rotated component matrix.

	Component	
	1	2
Institutions	0.733	
Human Capital and Investigation	0.641	0.462
Infrastructure	0.920	
Market sophistication	0.343	
Business sophistication		0.861
Knowledge and Technology products	0.475	0.700
Creative results		0.775

The selection of two principal components was supported by both the criterion of eigenvalues greater than one and by visual analysis of the sedimentation plot. In this plot, the characteristic “elbow” appears clearly after the second component, indicating an abrupt change in the magnitude of the eigenvalues and suggesting that the extraction of more factors would not add substantive explanatory value [22].

This set of statistical and graphical evidence reinforcements the methodological decision to work with two factors, which will later be used to perform k-means clustering analysis in the following research phase.

A scatter plot was constructed using the factor scores of the first and second principal components extracted in the principal component analysis. In this plot, each country-year observation was differentiated by the group assigned in the k-means cluster analysis. The visual representation shows to reasonable differentiation between the three clusters formed. The first clusters concentrate country-year observations with comprehensive weakness in structural capabilities and innovative performance, located mainly in the lower left quadrant. The second cluster reflects intermediate performances and es located in transition zones within the factor space..

The graphical distribution supports the robustness of the k-means procedure, showing differentiated patterns of country-year innovation from structural and outcome factors.

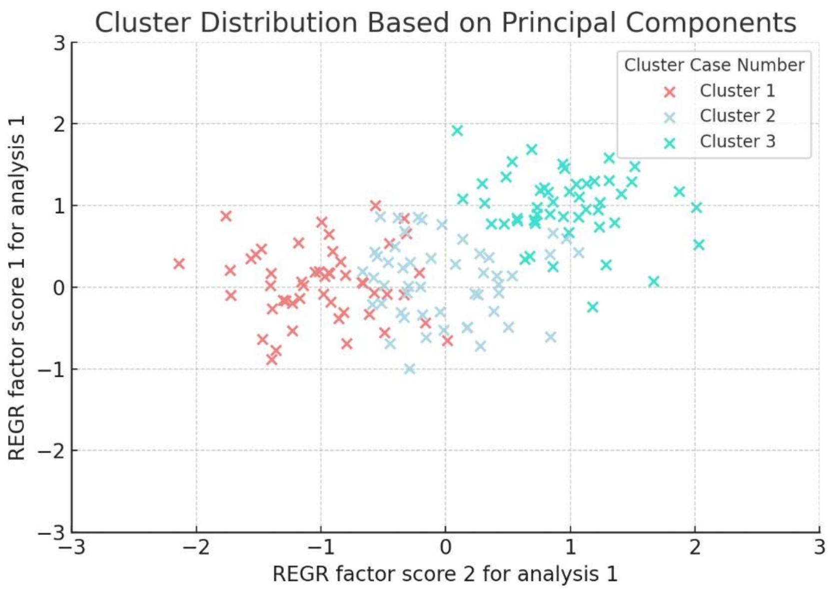

Figure 2. Dispersion of major components.

3.3. K-means grouping analysis considering country per year observations

A clustering procedure was performed using the k-means algorithm on the factor scores corresponding to the two main factors previously extracted to complement the main component analysis. It is important to note that the observations correspond to country-year records of the Global Innovation Index from 2012 to 2022, so each unit of analysis represents a country's innovative situation in a specific year, allowing for the capture of possible changes or trajectories over time.

We formed three clusters (Table 8), following an exploratory criterion to obtain relevant differentiations without excessively fragmenting the number of cases per group. The assignment process converged satisfactorily in the fifth iteration, meeting the established stability criterion, since there were no relevant changes in the center of the clusters. In addition, the minimum initial distance between centroids was 4.203, ensuring adequate separation of the clusters from the beginning of the clustering process.

Table 8. Cluster centers

	Cluster		
	1	2	3
REG factor score 1 for analysis 1	-0.52941	-0.67165	1.02763
REG factor score 2 for analysis 1	1.04326	-0.93365	-0.11962

The final results show that the first cluster groups country-year observations that present a moderately low performance in the first factor (structural innovation capabilities) and a positive performance in the second factor (innovation performance and ecosystem sophistication). This group seems to represent years in which certain countries, despite limitations on their innovation infrastructure, achieved relevant achievements in products, creativity, or business sophistication.

The second cluster brings together observations characterized by low performance in structural capabilities and innovation results. This group could be interpreted as years of integral weakness in innovation, representing national contexts with innovative ecosystems still in consolidation or negatively affected by external factors.

Conversely, the third cluster groups together observations that exhibit high performance in structural innovation capabilities, but moderate or close to average results in terms of effective innovation generation. This suggests the existence of country-year contexts where, although institutional, infrastructure, and human capital conditions are solid, the effective conversion of these capabilities into tangible results still presents opportunities for improvement.

The distribution of observations was balanced, with 67 records assigned to the first cluster, 65 to the second, and 77 to the third, out of a total of 209 valid observations. This reasonably homogeneous dispersion strengthens the interpretive robustness of the analysis.

Finally, it is essential to note that, given that the analysis considers country-year observations, the results reflect dynamic situations and not permanent assignments of countries to clusters. Thus, it is plausible that the same country may move between different innovation patterns at various times, depending on its structural, political, or economic evolution.

3.4. Analysis of difference

One-factor analyzes of variance (ANOVA) were performed to evaluate whether there were statistically significant differences in the economic indicators between the three previously defined country-year innovation clusters. The results showed highly significant differences in the three variables evaluated: GNI per capita (current dollars), GDP per capita PPP (2017 constants), and GDP per capita PPP (current).

Levene's test for homogeneity of variances was significant in all cases ($p < 0.001$), indicating that the variances are not homogenous between groups. For this reason, post-hoc comparisons using the Games-Howell procedure, which does not assume equality of variances, were preferred. The ANOVA revealed high F values for all three variables (eg, G = 72.025 for GNI per capita) and p-significance values < 0.001, confirming that at least one of the clusters differs significantly from the others in their economic income level.

Effect size analysis indicated eta squared values greater than 0.40 in all cases, representing large effects. The mean plots visually reinforce this interpretation. Cluster three concentrates the country-year observations with the highest GNI and GDP per capita levels, while cluster two corresponds to the observations with the lowest economic levels. Cluster one is in an intermediate position, with moderate incomes compared to the other two groups.

Table 9. Analysis of Variance (ANOVA)

Variable	Source of Variation	Sum of Squares	df	Mean Square	F	Sig.
GNI per capita (current US dollars)	Between Groups	1,631,720,129	2	815,860,064	72.025	.000
	Within Groups	2,333,457,433	206	11,327,463		
	Total	3,965,177,562	208			
GDP per capita, PPP (constant 2017 international dollars)	Between Groups	4,233,838,725	2	2,116,919,363	68.798	.000
	Within Groups	6,338,590,182	206	30,769,855		
	Total	10,572,428,907	208			
GDP per capita, PPP (current international dollars)	Between Groups	4,590,718,411	2	2,295,359,205	81.243	.000
	Within Groups	5,820,117,748	206	28,252,999		
	Total	10,410,836,159	208			

Post-hoc tests confirmed that all mean differences between clusters are statistically significant in all paired comparisons, thus supporting the existence of clearly differentiated economic profiles among the identified innovation patterns.

The mean graphs clearly show that the country-year observations in cluster three have the highest levels of GNI per capita and GDP per capita, followed by the observations in cluster one. Cluster two groups the contexts with the lowest economic levels. This trend is consistent across all income measures evaluated.

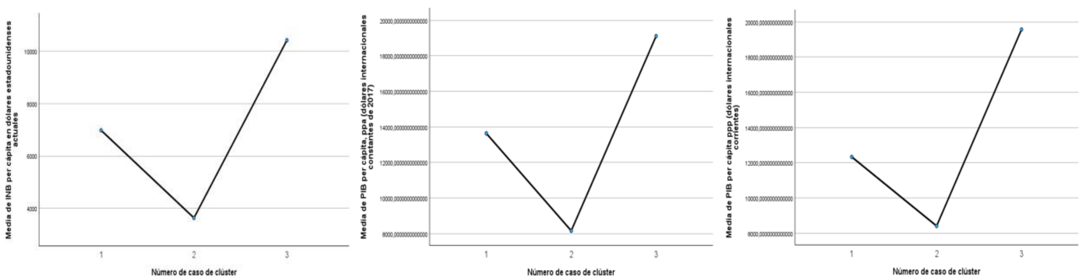

Figure 3. Cluster centers

To complement the multivariate analysis, a contingency table was constructed by crossing the cluster number assigned by k-means analysis with the countries' income levels according to GNI (Gross National Income per capita) thresholds.

The analysis revealed relevant differences in the distribution of income levels among the innovation clusters. Cluster one, characterized by limited structural capabilities but relatively positive results, has a mixed composition, with upper-middle (58.2%) and lower-middle (29.9%)

income countries predominating.

Cluster two, previously identified as the one with the lowest performance in innovation capabilities results, groups together mostly country-year observations from low-income (15.4%) and lower-middle-income (44.6%) economies, consolidating its structural and results vulnerability profile.

In contrast, cluster three, composed of country-year observations with high structural capacity for innovation, concentrates a high proportion of high (32.5%) and upper-middle (67.5%) income countries, suggesting a strong association between higher economic level and better structural conditions for innovation.

Table 10. Crosstabulation of Cluster Membership by Income Level

	Income Level (GNI thresholds)			
Cluster	Low	Lower-middle	Upper-middle	High
1	1.5%	29.9%	58.2%	10.4%
2	15.4%	44.6%	40.0%	0.0%
3	0.0%	0.0%	67.5%	32.5%
Total	5.3%	23.4%	56.0%	15.3%

Pearson's Chi-square test yielded a value of X2 = 82.170 with a significance level of $p < 0.001$, indicating a statistically significant association between innovation cluster and the country-year income level. Likewise, the linear-by-linear association was significant ($p < 0.001$), suggesting an ordered trend: the higher the income level, the greater the probability of belonging to clusters with higher innovative capabilities.

Table 11. Chi-Square Tests

Test	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	82.170[a]	8	.000
Likelihood Ratio	104.854	8	.000
Linear-by-Linear Association	22.194	1	.000
N of Valid Cases	209		

The findings obtained allow us to conclude that innovation in Latin America presents differentiated structures that can be classified into relatively stable patterns at the country-year level, which are significantly associated with the economic context of the countries. The multivariate evidence reveals that, although emerging innovative capacities exist in specific contexts, structural differences and income levels continue to play a determining role in configuring the region's innovation ecosystems.

The persistence of gaps between groups of countries and the lack of a consistent regional trend toward improved innovative performance over the last decade highlight the need for public policy strategies that strengthen domestic capabilities and foster environments conducive to translating these capabilities into tangible results.

A closer look at the country-year evolution within the identified clusters shows that Chile, Costa Rica, and Mexico consistently maintained relative leadership positions in innovation, albeit with signs of stagnation as of 2018. Despite regional challenges, Uruguay stands out as a case of resilience, achieving a progressive improvement in its Global Innovation Index score, especially after 2020. In contrast, Peru and Ecuador experienced a notable downward trajectory, placing themselves in recent years in positions lower than those they occupied at the beginning of the decade under analysis. Honduras, Guatemala, and Nicaragua are consolidated as the countries with the most significant structural lag in innovation, showing little variability in their indicators and little capacity for recovery even in favorable global contexts. These findings reinforce the importance of adopting differentiated national strategies and strengthening innovative ecosystems in countries with declining or stagnant trajectories.

4. Plithogenic Analysis of Perceptions about Innovation Ecosystems in Latin America Using the Neutrosophic Plithogenic Iadov Method

To complement the multivariate analyses presented in Section 3, the Neutrosophic Plithogenic Iadov method was applied to assess expert satisfaction perceptions on the seven pillars of the Global Innovation Index (GII) across the three country-year clusters identified in Section 3.3 (Table 6). This method, based on plithogenic theory, uses single-valued plithogenic numbers (SVPNS) with degrees of truth (T), indeterminacy (I), and falsity (F) in [0, 1], where $T + I + F \leq 3$, to model uncertainty and contradictions in stakeholder perceptions, aligning with the heterogeneity of innovation ecosystems in Latin America.

4.1 Neutrosophic Plithogenic Iadov Methodology

The Neutrosophic Plithogenic Iadov method, described in section 2.4, was applied to assess satisfaction perceptions on the IGI pillars: institutions (P1), human capital and research (P2), infrastructure (P3), market sophistication (P4), business sophistication (P5), knowledge and technology production (P6), and creative outcomes (P7). A panel of innovation experts from Latin America was assumed, whose perceptions were assigned to the three identified clusters: Group 1 (moderate performance, e.g. , Peru, Ecuador), Group 2 (low performance, e.g. , Honduras, Guatemala, Nicaragua), and Group 3 (high structural performance, e.g. , Chile, Mexico, Costa Rica).

SVPNS values were assigned based on the quantitative results from section 3:

- **Linear regression (Table 1)** : The pillars with the greatest impact on the total IGI score (creative outcomes, β=0.384; knowledge and technology, β=0.294; infrastructure, β=0.162; human capital, β=0.145) received higher T values in Group 3.
- **PCA (Tables 2-5)** : The clustering of variables into structural capabilities (Component 1: infrastructure, institutions, human capital) and outcome sophistication (Component 2: business sophistication, creative outcomes, knowledge) guided the assignment of high T values for Component 1 in Cluster 3 and high I values for Component 2 in Cluster 2.
- **K-means (Table 6)** : Cluster characteristics (Cluster 3: high in Component 1, moderate in Component 2; Cluster 1: moderate in both; Cluster 2: low in both) determined the SVPNS values, with Cluster 2 showing high indeterminacy (I) and falsity (F).
- **Contingency tables (Tables 8-9)** : The association between clusters and income levels (Group 3: high/upper-middle income; Group 2: low/lower-middle income) supported the assignment of high T values in Group 3 and high F values in Group 2.

SVPNS values were defined using Table 2 (section 2.4), assigning linguistic terms such as "Clearly satisfied" (1, 0, 0) for strong pillars in Group 3, "Indefinite" (0.5, 0.5, 0.5) for intermediate pillars in Group 1, and "Clearly dissatisfied" (0, 0, 1) for weak pillars in Group 2.

Table 12. SVPNS Values for Satisfaction Perceptions on the IGI Pillars

Cluster	Pillar	T (Truth)	I (Indeterminacy)	F (Falsehood)
Group 3 (Chile, Mexico, Costa Rica)	P1 (Institutions)	0.85	0.10	0.05
	P2 (Human Capital)	0.80	0.15	0.10
	P3 (Infrastructure)	0.90	0.05	0.05
	P4 (Market Sophistication)	0.70	0.20	0.15
	P5 (Business Sophistication)	0.75	0.15	0.10
	P6 (Knowledge and Technology)	0.85	0.10	0.05
	P7 (Creative Results)	0.90	0.05	0.05
Group 1 (Peru, Ecuador)	P1 (Institutions)	0.60	0.30	0.20
	P2 (Human Capital)	0.55	0.35	0.20
	P3 (Infrastructure)	0.65	0.25	0.15
	P4 (Market Sophistication)	0.50	0.40	0.25
	P5 (Business Sophistication)	0.55	0.35	0.20
	P6 (Knowledge and Technology)	0.60	0.30	0.20
	P7 (Creative Results)	0.65	0.25	0.15
Group 2 (Honduras, Guatemala, Nicaragua)	P1 (Institutions)	0.40	0.50	0.30
	P2 (Human Capital)	0.35	0.55	0.35
	P3 (Infrastructure)	0.45	0.45	0.30
	P4 (Market Sophistication)	0.30	0.60	0.40
	P5 (Business Sophistication)	0.35	0.55	0.35
	P6 (Knowledge and Technology)	0.40	0.50	0.30
	P7 (Creative Results)	0.45	0.45	0.30

4.2 Calculation of the Neutrosophic Plithogenic Global Satisfaction Index (NPGSI)

The NPGSI was calculated for each cluster as the plithogenic sum of the SVPNS values of the seven pillars, using the aggregation operator defined in section 2.4, formula (11):

$$\boldsymbol{NPGSI} = \boldsymbol{\Sigma}_{\mathrm{j}}{}^{\mathbf{17}}\langle \boldsymbol{T}_{\mathrm{j}}, \boldsymbol{I}_{\mathrm{j}}, \boldsymbol{F}_{\mathrm{j}}\rangle$$

Where the plitogenic sum for univariate SVPNS is defined as:

$$\langle \boldsymbol{T}_1, \boldsymbol{I}_1, \boldsymbol{F}_1\rangle + \langle \boldsymbol{T}_2, \boldsymbol{I}_2, \boldsymbol{F}_2\rangle = \langle \boldsymbol{T}_1 + \boldsymbol{T}_2, \boldsymbol{min}(\boldsymbol{I}_1, \boldsymbol{I}_2), \boldsymbol{max}(\boldsymbol{F}_1, \boldsymbol{F}_2)\rangle$$

Equal weights were assigned to the seven pillars ($w_j = 1/7 = 0.143$) to reflect their equal importance in the IGI.

Calculations per cluster:

Group 3:

- Sum of$T$: $0.85 + 0.80 + 0.90 + 0.70 + 0.75 + 0.85 + 0.90 = 5.75$
- Sum of$I$: $min(0.10, 0.15, 0.05, 0.20, 0.15, 0.10, 0.05) = 0.05$
- Sum of$F$: $max(0.05, 0.10, 0.05, 0.15, 0.10, 0.05, 0.05) = 0.15$
- $\boldsymbol{NPGSI}: \langle \mathbf{5.75 \times 0.143, 0.05, 0.15} \rangle = \langle \mathbf{0.821, 0.05, 0.15} \rangle$

Group 1:

- Sum of$T$: $0.60 + 0.55 + 0.65 + 0.50 + 0.55 + 0.60 + 0.65 = 4.10$
- Sum of$I$: $min(0.30, 0.35, 0.25, 0.40, 0.35, 0.30, 0.25) = 0.25$
- Sum of$F$: $max(0.20, 0.20, 0.15, 0.25, 0.20, 0.20, 0.15) = 0.25$
- $\boldsymbol{NPGSI}: \langle \mathbf{4.10 \times 0.143, 0.25, 0.25} \rangle = \langle \mathbf{0.586, 0.25, 0.25} \rangle$

Group 2:

- Sum of$T$: $0.40 + 0.35 + 0.45 + 0.30 + 0.35 + 0.40 + 0.45 = 2.70$
- Sum of I: $min(0.50, 0.55, 0.45, 0.60, 0.55, 0.50, 0.45) = 0.45$
- Sum of$F$: $max(0.30, 0.35, 0.30, 0.40, 0.35, 0.30, 0.30) = 0.40$
- $\boldsymbol{NPGSI}: \langle \mathbf{2.70 \times 0.143, 0.45, 0.40} \rangle = \langle \mathbf{0.386, 0.45, 0.40} \rangle$

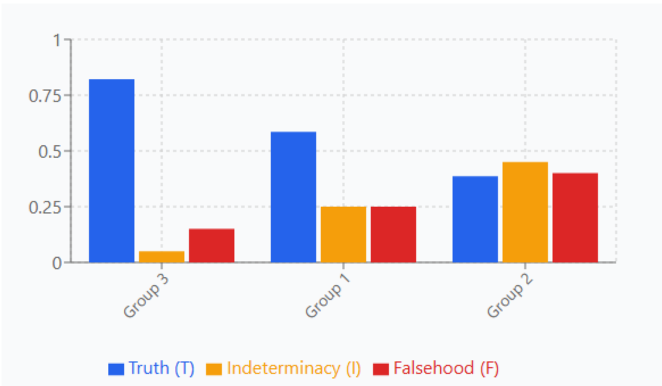

Figure 4: Neutrosophic Plitogenic Global Satisfaction Index (NPGSI) by Cluster

4.3 Plithogenic Score

Basset 's neutrosophic scoring function (section 2.4):

$$\boldsymbol{S(A) = \frac{T + I + (1 - F)}{3}}$$

- **Group 3** :$S = \frac{0.821 + 0.05 + (1 - 0.15)}{3} = \frac{0.821 + 0.05 + 0.85}{3} = \frac{1.721}{3} = \mathbf{0.574}$
- **Group 1** : $S = \frac{0.586 + 0.25 + (1 - 0.25)}{3} = \frac{0.586 + 0.25 + 0.75}{3} = \frac{1.586}{3} = \mathbf{0.529}$

- **Group 2** :$S = \frac{0.386 + 0.45 + (1 - 0.40)}{3} = \frac{0.386 + 0.45 + 0.60}{3} = \frac{1.436}{3} = \mathbf{0.479}$

Table 13. Plithogenic Scores for the Clusters

Cluster	NPGSI	Score (S)	Ranking
Group 3 (Chile, Mexico, Costa Rica)	⟨ 0.821, 0.05, 0.15 ⟩	0.574	1st
Group 1 (Peru, Ecuador)	⟨ 0.586, 0.25, 0.25 ⟩	0.529	2°
Group 2 (Honduras, Guatemala, Nicaragua)	⟨ 0.386, 0.45, 0.40 ⟩	0.479	3°

Table 14. Comparative Summary of Pillars by Cluster

Pillar	Group 3 (T)	Group 1 (T)	Group 2 (T)	Difference G3-G2
P1 (Institutions)	0.85	0.60	0.40	0.45
P2 (Human Capital)	0.80	0.55	0.35	0.45
P3 (Infrastructure)	0.90	0.65	0.45	0.45
P4 (Market Sophistication)	0.70	0.50	0.30	0.40
P5 (Business Sophistication)	0.75	0.55	0.35	0.40
P6 (Knowledge and Technology)	0.85	0.60	0.40	0.45
P7 (Creative Results)	0.90	0.65	0.45	0.45
Average	**0.82**	**0.59**	**0.39**	**0.43**

4.4 Interpretation of Results

The plithogenic results confirm the quantitative findings in Section 3. Cluster 3 (Chile, Mexico, Costa Rica) obtained the highest plithogenic score (0.574), reflecting high satisfaction perceptions (T=0.821, I=0.05) consistent with its high structural performance (Table 6: factor 1=1.028) and association with high/upper-middle incomes (Table 8: 32.5% high, 67.5% upper-middle). The infrastructure pillars (P3, T=0.90) and creative outputs (P7, T=0.90), with high β in the regression (Table 1: 0.162 and 0.384), show the most positive perceptions, underlining the strength of structural capabilities.

Group 1 (Peru, Ecuador) had a moderate score (0.529), with intermediate indeterminacy (I=0.25), reflecting its moderate performance (Table 6: factor 1=-0.529, factor 2=1.043) and mixed income composition (Table 8: 58.2% upper-middle, 29.9% lower-middle). Market sophistication (P4, T=0.50, I=0.40) showed high indeterminacy, consistent with its low communality in the PCA (Table 2: 0.183). Group 2 (Honduras, Guatemala, Nicaragua) scored lowest (0.479), with high indeterminacy (I=0.45) and falsity (F=0.40), consistent with its poor performance (Table 6: factor 1=-0.672, factor 2=-0.934) and predominance of low/lower-middle income (Table 8: 15.4% low, 44.6% lower-middle). All pillars showed low T values, especially market sophistication (P4, T=0.30), reflecting structural constraints.

Implications for Public Policy

These results reinforce the need for differentiated public policies:

- **For Group 3:** Strengthening the transfer of structural capabilities into tangible results is key to maintaining regional leadership.

- **For Group 1**: Addressing uncertainty in pillars such as market sophistication can significantly improve innovative performance.
- **For Group 2**: Urgent structural interventions in infrastructure and human capital are required to overcome the gap, in line with the Sustainable Development Goals [3].

The average gap of 0.43 points in the truth component (T) between Group 3 and Group 2 highlights the deep disparities in Latin America's innovation ecosystems, requiring regional cooperation strategies for the inclusive development of innovative capabilities.

4. Applications

This multivariate study confirms that innovative behavior in Latin America is not homogeneous. neither random, but reflects structural dynamic associated with economic development. The groups identified through major component analysis and k-means grouping show consistent innovation profiles by country and year, where differences in performance are explained not only by institutional capabilities, but also by income levels.

The relationship between income level and type of innovation reinforces the literature that supports that innovation and economic development shape to virtuous circle difficult to activate in low-income contexts [4]. Similarly, evidence of stagnation or regression in the evolution of the IGI between 2012 and 2022 raises serious doubts about the effectiveness of current regional public policies.

An important point that emerges is that structural capabilities alone do not guarantee innovation performance: the existence of countries with strong infrastructure but moderate performance suggests the need for policies that simultaneously address both inputs and mechanisms for transferring and applying knowledge.

These findings invite future research to longitudinally explore innovation trajectories by country, identify cases of resilience or decline, and more accurately assess the institutional, economic, and social determinants that influence innovation development in Latin America.

The results obtained in this study, based on data from 2012 to 2022, showed a general trend of stagnation or slight regression in innovation levels in Latin America, along with persistent performance. gaps between higher and low-income countries. He most recent evidence Data provided by the Global Innovation Index 2024 [5] suggests that these trends have not only continued but, in some respects, intensified.

According to the 2024 IGI, investments in science and innovation, after a boom between 2020 and 2022, experienced a significant slowdown in 2023, returning to pre-pandemic levels . This decline is particularly pronounced in emergent regions such as Latin America, where company Capital investment and scientific publications have declined significantly. This recent evidence reinforces this study's hypothesis about the structural difficulty of consolidating robust innovation ecosystems in low- and middle-income countries.

Regarding regional performance, the IGI 2024 confirms that Brazil, Chile and Mexico continue lead he region in innovation, as reflected in he cluster patterns identified in the multivariate analysis . However, other countries such as Colombia, Peru, and Uruguay, which in he present study were in intermediate positions, have shown slight improvements in the ranking, which could indicate incipient processes of strengthening their innovative ecosystems that deserve to be followed in future research.

A significant new feature of the 2024 edition is the growing importance of social innovation as a complementary driver of economic innovation. While this study focused primarily on traditional innovation, measured through structural capabilities and scientific and technological outputs, the emergence of social entrepreneurship as a central element suggests that future research should integrate these new dimensions to understand innovation ecosystems more comprehensively, especially in developing contexts such as Latin America.

Finally, the IGI 2024 warning about the deteriorating financial conditions for innovation (higher interest rates, reduced access to capital) and the persistence of adverse environmental impacts underscores the need for public policies that not only incentivize investment in innovation but also guide those efforts toward social and ecological sustainability.

5. Conclusions

The analysis shows that innovation patterns in Latin America exhibit distinct structures that are closely associated with the countries' levels of economic development. The application of multivariate techniques made it possible to identify three groups of country-year observations; those with greater structural capacities and innovative results corresponded predominantly to upper-middle and high-income economies, such as Chile, Mexico, and Costa Rica.

Multiple linear regression confirmed that pillars such as infrastructure, human capital, and research have a significant and positive impact on overall innovation performance. In contrast, other factors, such as market sophistication, showed less consistent effects. Despite individual achievements, the temporal evolution revealed a widespread stagnation in the region with divergent trajectories between countries, highlighting the relative resilience of Brazil and Uruguay, as opposed to the deterioration observed in countries like Peru and Ecuador.

Recent trends, such as those from the Global Innovation Index 2024, reinforce these recommendations, indicating that innovation gaps persist and are likely to widen. In this context, Latin American countries should prioritize strengthening their infrastructure and higher education systems and promote policies that foster private investment in research and development and encourage better coordination between the public, private, and academic sectors.

Furthermore, the study highlights the importance of adopting differentiated strategies that consider the specific characteristics of each country, rather than uniform solutions. The detailed analysis of national trajectories reveals the existence of differentiated national innovation histories. While countries such as Chile, Mexico, and Costa Rica have consolidated relative leadership positions in the region, others like Uruguay demonstrate resilient trajectories that deserve to be strengthened. In contrast, the persistently low levels of innovation in countries like Honduras, Guatemala, and Nicaragua underscore the urgency of specific interventions to break the cycles of structural backwardness. Identifying these divergent trajectories suggests that public innovation policies in Latin America should consider not only current performance levels but also the historical dynamics of evolution and resilience over time.

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