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A multivariate framework for measuring international mobility in tertiary education with neutrosophic sentiment assessment

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Abstract: International mobility of tertiary education is vital for countries engaged in innovative educational research and those wishing to stay ahead in the field. However, cross-national comparisons face a challenge in methodology induced by the phenomenon's multi-dimensionality. This study analyzes the international mobility of tertiary education in 29 countries from 2013 to 2020 using international students as a percentage of enrollment as a primary dependent variable. The goal is to evaluate trends across nations and subsequently propose a composite index of the multi-dimensional phenomenon. A variety of multivariate analytical techniques were employed; for example, STATIS (Structuring de Tableaux À Trois) Statistics Indices determined a composite structure across countries over time, while hierarchical cluster analysis revealed four clusters of countries with distinguished trends of international mobility in tertiary education. Results confirm the existence of significant trends across time for international students' percentage structure, with 2017 and 2020 being essential years. Our main finding is the International Mobility in Tertiary Education Index (IMIET), determined with four dimensions: baseline, dynamism, coherence, and regional differentiation. For example, Latin America and Asia present low levels of baseline and dynamism, which limits their international competitiveness potential; at the regional level, Oceania excels in IMIET segments like dynamism and coherence, suggesting the related public policies developed there in recent years. Additionally, a neutrosophic sentiments assessment allows for a qualitative evaluation of international scholars via truth indeterminacy and falsity components to provide more in-depth assessments of International Mobility trends while exploring qualitative satisfaction, research impediments, and expectations in indeterminacy.

Keywords: International Student Mobility; Higher Education; Multivariate Analysis; Synthetic Index; Neutrosophic Assessment of Sentiments.

1. Introduction

The internationalization of higher education and the entailed international mobility process has become a complex and important phenomenon in recent decades, impacting the transformation of educational systems worldwide [1,2]. Regardless of who undertakes international mobility (students, academics, or researchers), the concept has evolved into a multifaceted and continuously complex process, redefined, involving and reflecting political dynamics, economic aspects, sociocultural issues, and academic considerations [3–5]. In this context, international student mobility appears as a strategic component that impacts the development of advanced human capital and promotes academic innovation [6,7]. Particularly among OECD countries and emerging economies, the ability to attract and retain international students has become an important indicator of global positioning [8]. However, recent trends reveal certain challenges: while internationalization has been promoted as a tool to foster intercultural understanding and global cooperation [2], it has progressively shifted towards a market-driven logic focused on competition for resources and academic prestige [9,10]. These dynamics vary significantly across regions, institutional types, and education policy models. Additionally, recent approaches such as block-based immersive learning models [11] seek to improve the success of international students by fostering their experience in these contexts, while also raising new challenges related to student adaptation and equity.

In summary, this study aims to analyze international mobility in 29 countries between 2013 and 2020 using multivariate analysis techniques. Specifically, it proposes: (i) using the STATIS method to obtain the structural trade-off between annual mobility patterns; (ii) visualizing and segmenting countries' behaviors through Principal Component Analysis (PCA) and biplot representations; (iii) classifying countries into groups by applying hierarchical clustering ; (iv) constructing and validating the International Mobility Index in Tertiary Education (IMIET), integrating the base-level dimensions (related to the variable "percentage of international students enrolled in the destination country"), dynamism, structural coherence, and regional differentiation; (v) to compare the performance of international mobility at the country and regional levels—North America, Latin America, Europe 1 (Northern, Southern, and Western Europe), Europe 2 (Eastern Europe), Asia, and Oceania—based on the synthesized indicators; and (vi) to apply a neutrosophic sentiment assessment to analyze international students' subjective perceptions, considering components of truth, indeterminacy, and falsity, in order to complement the quantitative analysis with a qualitative perspective that captures the uncertainty and contradictions in mobility experiences.

This study is divided into the following sections. Section 2 describes the dataset and the multivariate analysis methodologies used. Section 3 presents the results of the multivariate analyses and the IMIET index. Section 4 discusses the main findings. Section 5 presents the results of the neutrosophic sentiment assessment. Finally, Section 6 presents the study's conclusions and future work.

2. Materials and methods

2.1. Description of the dataset

- Dataset: International mobility data (percentage of foreign students in tertiary education) [12] for 27 OECD countries and 2 non-OECD countries.
- Period analyzed: 2013–2020.
- Number of countries: 29 selected countries with consistent data series.
- List of OECD countries: Australia, Austria, Canada, Chile, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States.
- List of non-OECD countries: Brazil and Bulgaria.

2.2. Methodology

This quantitative, exploratory, and comparative study seeks to identify structural patterns in international mobility in higher education in 29 countries (27 OECD countries, Brazil, and Bulgaria) and, based on this information, propose an international mobility index called IMIET. The methodological approach is based on the application of multivariate statistical techniques such as

STATIS, hierarchical clustering, principal components analysis, and biplot to summarize and interpret the behavior of these countries between 2013 and 2020.

First, the STATIS method was applied to the study dataset to capture the structural interaction of the multiple annual matrices, providing a unified view of the phenomenon. Principal Components Analysis (PCA) was then used to reduce dimensionality (number of variables) and visualize country trajectories, while hierarchical clustering techniques helped identify groups of countries with similar mobility behaviors. Finally, a synthetic index called the International Mobility Index in Tertiary Education (IMIET) was constructed, which integrates four key dimensions: base level, dynamism, structural coherence, and regional differentiation. This approach allows for comparisons across the study countries and contributes to our understanding of the processes involved in aspects of international mobility in tertiary education.

2.2.1. Statistics

The STATIS method (Structure of Tableaux À Trois Indices de Statistique), was a method originally developed by [13], first described by [14] and further developed by [15] and [16], constitutes a multivariate approach aimed at jointly analyzing multiple structured quantitative data matrices on the same set of individuals. The procedure has three main phases: (i) the construction of the vector correlation matrix (RV matrix) between individual tables to assess their structural similarity; (ii) the analysis of the interstructure by Principal Component Analysis (PCA) on the RV matrix to identify a common trade-off between the tables; and (iii) the projection of the individuals onto the trade-off space, which allows to interpret their relative positions as observed. STATIS has been used in numerous fields, such as health sciences [17-19], atmospheric sciences [20], hydrology [21], chemometrics and process monitoring [22], neuroscience [23,24] and genetics [25] among other areas.

From a three-way table analysis perspective, the process comprises the same I individuals and J variables observed under K different conditions or occasions (in this case years) for which the following points are met

Let be $K$the number of matrices (data matrices), each with dimension $I \times J$:

$$X^{(k)} \in \mathbb{R}^{I \times J}, k = 1,2,..,K \tag{1}$$

For this study:

- I:countries
- J:number of indicators
- K:years

Each matrix is normalized (or optionally column-centered), resulting in the form:

$$Z^{(k)} = \frac{X^{(k)} - mean(X^{(k)})}{sd(X^{(k)})} \tag{2}$$

For each k, the double scalar product matrix (country similarity matrix) is calculated as:

$$S^{(k)} = Z^{(k)} Z^{(k)^T} \tag{3}$$

where $Z^{(k)^T}$is the transpose of $Z^{(k)}$obtaining Kmatrices of dimension $I \times I$.

From each similarity matrix $S^{(k)}$, we obtain the similarity matrix between tables (RV matrix), derived from vector correlation analysis [26,27].

Then, for two time points $k_1$andk_2

$$RV(k_1, k_2) = \frac{\langle S^{(k_1)}, S^{(k_2)} \rangle_F}{\|S^{(k_1)}\|_F \cdot \|S^{(k_2)}\|_F} \tag{4}$$

Where denotes the $\langle \cdot , \cdot \rangle_F$Frobenius inner product.

By applying Principal Component Analysis (PCA) to the RV matrix, we obtain the weights α_k that maximize the commitment, resulting in the commitment matrix S_{comp} that summarizes all the years:

$$S_{comp} = \sum_{k=1}^{K} \alpha_k S^{(k)} \tag{5}$$

Finally, applying PCA to the commitment matrix S_{comp}:

$$S_{comp} = \mathbb{U}\Lambda\mathbb{U}^T \tag{6}$$

Where the eigenvectors $\mathbb{U}$ represent the coordinates of the countries in the STATIS commitment space.

2.2.2. Cluster analysis

Cluster analysis involves a wide range of techniques aimed at characterizing groups present in data based on individuals' behavior across multiple variables [28]. Hierarchical clustering, based on Ward's method [29], is recognized for its ability to generate well-defined and distinct clusters [30]. The analysis constructs a nested sequence of partitions by successively merging smaller clusters (agglomerative approach) or splitting larger ones (divisive approach). This process generates a dendrogram (a tree-like diagram that visually represents the relationships and proximities between clusters) [31], which facilitates the identification of the underlying structure and the optimal number of groups within the data.

2.2.3. Biplot analysis

A Biplot [32] is a graphical tool that allows multivariate data to be represented simultaneously. While a conventional scatter plot shows the relationship between two variables, the Biplot extends this concept by allowing both individuals and variables to be visualized on the same plane, facilitating the joint interpretation of their relationships. This technique was later extended and applied in various contexts [33]. In this study, an HJ-Biplot [34,35] will be applied to the results of the trade-off matrix obtained from STATIS.

2.2.4. The synthetic index

The construction of a synthetic index seeks to summarize the multidimensional nature of international mobility in tertiary education into a single interpretable metric. This approach is consistent with methodologies applied in fields such as sustainability assessment [36] and multidimensional well-being analysis [37], where the complexity of the phenomena requires integrated measures rather than isolated indicators. Following the guidelines established by [38], the process begins with the careful selection and normalization of relevant variables. In our case, these variables represent distinct aspects of international student mobility in 29 countries during the period 2013–2020. Each variable was standardized to ensure comparability across units and years. Once standardized, the variables were combined using weighted aggregation. Component weights were determined based on statistical and conceptual relevance, ensuring an objective balance between the base component, dynamism, structural coherence, and cluster member differentiation. This methodology is similar to the practice of combining multiple indicators into a composite index, while minimizing arbitrariness, as described in [39].

The construction of the index follows three phases:

1. Dimension selection and normalization: Variables were selected based on their relevance and standardized to eliminate scale differences.

2. Weight Assignment: Inspired by entropy methods and rough set theory [40], weights were objectively assigned to reflect the variability and importance of each dimension.
3. Aggregation: A synthetic score was calculated as a linear combination of the weighted indicators, assimilating the practices observed in the Sustainable Society Index and the Multidimensional Well-being Index of the European Union [37].

This theoretical proposal for the creation of a synthetic index [38] allows the International Mobility Index in Tertiary Education (IMIET) to incorporate both the base levels related to the average and the dynamic component of mobility, maintaining the transparency of the methodology and allowing replicability and comparability between countries. These synthetic indices, as highlighted in [41], provide robust tools for the interpretation of results for policy analysis and strategic planning, offering a simplified but valuable representation of complex social phenomena.

2.3. Sentiment analysis.

Sentiment analysis involves the application of natural language processing tools, along with textual analysis and computational linguistics techniques, to unravel and extract subjective information from diverse sources. [42] In the field of text mining, this methodology has the potential to address massive data polarity classification.

There are several fundamental categories in sentiment analysis, including lexical affinity, statistical methods, and conceptual techniques. However, the task of assessing sentiments, whether those of an individual or a group, is inevitably linked to the complexity imposed by the inherent subjectivity of the process. This is because emotional states are often ephemeral and can manifest one way in an instant, only to transform into something completely different shortly after.

Regarding measurement scales, experts emphasize the importance of incorporating a neutral option, given that an individual may not be able to clearly identify their emotional state as positive or negative, or may be in a state of neutrality that doesn't clearly align with either option. Neutrosophy is especially relevant in this regard, as its theory encompasses not only positive and negative aspects, but also neutrality. This perspective is particularly useful when examining the connotation of words in a text, which adds an additional layer of complexity to the process.

Neutral algebra generated by the combination function in Prospector

For a given natural number $n > 0$, NeutroGroup is defined from the Prospector combinator function. Prospector is the well-known expert system used to model mining problems [43]. The set NeutroGroup consists of all integers between $-n$and $n$plus the symbolic element I to represent indeterminacy. This is $NG_5 = \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, I\}$ and is used. This is defined according to the following $\oplus_5$Cayley table:

Table 1. Cayley table corresponding to $\oplus_5$. Source: [44].

$\oplus_5$	-5	-4	-3	-2	-1	0	Yo	1	2	3	4	5
-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	Yo
-4	-5	-5	-5	-5	-4	-4	-4	-4	-3	-2	0	5
-3	-5	-5	-4	-4	-4	-3	-3	-2	-1	0	2	5
-2	-5	-5	-4	-3	-3	-2	-2	-1	0	1	3	5
-1	-5	-4	-4	-3	-2	-1	-1	0	1	2	4	5
0	-5	-4	-3	-2	-1	0	Yo	1	2	3	4	5
Yo	-5	-4	-3	-2	-1	Yo	Yo	Yo	Yo	Yo	Yo	Yo
1	-5	-4	-2	-1	0	1	Yo	2	3	4	4	5
2	-5	-3	-1	0	1	2	Yo	3	3	4	5	5
3	-5	-2	0	1	2	3	Yo	4	4	4	5	5
4	-5	0	2	3	4	4	Yo	4	5	5	5	5
5	Yo	5	5	5	5	5	Yo	5	5	5	5	5

$\oplus_5$It satisfies the properties of commutativity and associativity and has 0 as its null element. Furthermore, it satisfies each of the following properties:

- If $x, y < 0$then $x \oplus_5 y \leq min(x, y)$,
- If $x, y > 0$then $x \oplus_5 y \geq max(x, y)$,
- If $x < 0$and $y > 0$or if $x > 0$and $y < 0$, then we have $min(x, y) \leq x \oplus_5 y \leq max(x, y)$.
- $\forall x \in G, x \oplus_5 0 = x$.
- $(-5) \oplus_5 5 = 5 \oplus_5 (-5) = I$.

Sentiment analysis, using the neutrosophic method, focuses on assessing integrity, transparency, and accountability within organizations. Using this theory, opinions and perceptions are examined by considering degrees of positivity, negativity, and indeterminacy. This approach not only captures clear sentiments, such as positive and negative ones, but also addresses those that are neutral or ambiguous, thus achieving a more accurate assessment and a better understanding of how these aspects are perceived in the organizational environment.

This method, particularly effective in the analysis of short, informal texts, as described in the technique mentioned above, requires the identification of a set of words that are classified as positive, negative, or neutral, each with a strength value evaluated on a range from -5 to 5, or marked as indeterminate. Indeterminacy occurs when it is not possible to clearly decipher the individual's thinking on the subject in question, which may occur due to a lack of clarity in the semantics of the text or because the text is unintelligible. Furthermore, in certain cases, extreme evaluations of positivity (+5) and negativity (-5) may be presented in the same text for the same variable, which generates a contradiction that is classified as indeterminate, marked with the letter I. This indeterminacy may have different origins, which becomes evident when the function used in the PROSPECT expert system, which evaluates the degree of evidence of an expert on a particular aspect, finds maximum evidence but in opposite directions for two different aspects.

This method, which borrows some elements from the SentiStrength sentiment strength detection algorithm [45], allows terms related to the analyzed variables to be classified as Positive, Negative, or Neutral from a list using linguistic values. Each of these terms is associated with a value between -5 and 5, or even 1, depending on the intensity of its positive or negative charge. For example, the term "like" increases its positive value if expressed as "I like it a lot," while "I don't like it" becomes more negative when expressed as "I don't like it a lot." What applies is that for the word "much " or "mucho" that modifies one of the positive or negative classifier words, is used $x \oplus_5 x$, and for "too" $x \oplus_5 x \oplus_5 x$, where $x$is the value associated with the word. For example, $x > 0$it results in "very" with an even more positive value. On the other hand, when $x < 0$, the result is more negative.

Also, the modification of "quite" is converted to $\left[sig(x)\sqrt{|x|}\right]$.

- They take into account words that invert the meaning of what is said. In this case, the sign is changed. For example, "I like" with a value of $x = 3$, when it comes to "I don't like" it is calculated as $x = -3$; both have the same strength, but with opposite meaning.
- This algorithm ignores highly complex cases, where there are exclamation or question marks, because we want to evaluate what members of the organization or clients write, if it makes sense, about each of the twelve aspects of ethics outlined in the previous points.
- Another aspect taken into account in the proposed algorithm taken from the previous one is the evaluation of emoticons.
- Spell checking also applies here.

The next step is the evaluation of a short, informal text written by a person. To do this, natural language processing is used to search for words that express feelings or opinions about each of the twelve aspects mentioned above. Let 's denote these aspects as :$V = \{v_1, v_2, \cdots, v_{12}\}$

Then, within the text processing, the words referring to each of these variables are identified. These words are identified with a value from -5 to 5 or I. Let's denote this as follows, for the i- th variable, the set $X_i$of word valuations that appear in the text:

$v_i \rightarrow X_i = \{x_{i1}, x_{i2}, \dots, x_{im_i}\}$, where$x_{ij}$ It is the set of elements between -5 and 5 or I, used to qualify the words that refer to the i- th variable.

Keep in mind that even evaluating each word individually can be complicated. For example, when modifiers like "very" appear, the value of the modified word changes. Also, when spelling errors make an evaluation illegible, it is necessary to use the value I. The final value associated with eachv_i is:

$$x_{total,i} = x_{i1} \oplus_5 x_{i2} \oplus_5 \dots \oplus_5 x_{im_i} \quad (1)$$

Let's keep in mind that we do not consider it convenient to obtain an aggregate ethical value for all variables since the separate value is more useful to have an idea of the individual opinion or feeling.

If we have a set of people whose opinion is being studied. Let's call this set of people by $P = \{p_1, p_2, \cdots, p_l\}$, so that the values are taken into account, $x_{total,i,j}$it is the total value of the i -th ethics variable in the organization, according to the jth person.

It is calculated:

$$\bar{x}_{total,i} = \frac{\sum_{j=1}^{l} x_{total,i,j}}{l} (2)$$

That is, the arithmetic mean of each of the variables is calculated.

3. Results

3.1. Application of STATIS to tertiary education mobility data.

The STATIS procedure consists of three main phases: (i) construction of the vector correlation matrix (VCM) between individual tables to assess their structural similarity; (ii) analysis of the interstructure using Principal Component Analysis (PCA) on the VCM to identify common trade-offs between tables; and (iii) projection of the individuals into the trade-off space, which allows to interpret their relative positions based on the observed multi-temporal or multi-conditional patterns. To perform the analyses on the collected data, the software R [46] and the packages ade4 [47,48] and FactoMineR [49] were used.

The results of the STATIS analysis offer an interpretation of the common structure of the international mobility data for the period 2013–2020. The interstructure graph (Figure 1a) shows the relationships between the different annual tables (years). The arrows in the figure point in similar directions, indicating strong structural coherence over the period 2013–2020. This coherence suggests that international mobility patterns did not undergo significant changes from one year to the next, and the eigenvalues confirm that most of the variability is concentrated along the first axis.

The typological values graph (Figure 1b) shows the squared cosines ($\cos^2$) that measure the quality of representation within the engagement space year by year. All years present values close to 1, indicating excellent representation. However, years such as 2017 and 2016 contribute more substantially to the engagement structure, while 2020 and 2019, although less influential, retain some relevance.

The compromise plot (Figure 2) shows the projection of countries onto this space, representing the common trends shared by all the data tables. Within the composite space, two countries stand out: Luxembourg and Australia, which deviate in opposite directions from the main cluster, being associated with different components (Luxembourg near the first component, and Australia between the first and second). This suggests that the two countries follow markedly different trajectories. The remaining countries form a more compact cluster near the origin of the coordinates, with behaviors aligned with the general structure, although some countries, such as Mexico, are observed in the opposite direction to Luxembourg.

(a) (b)

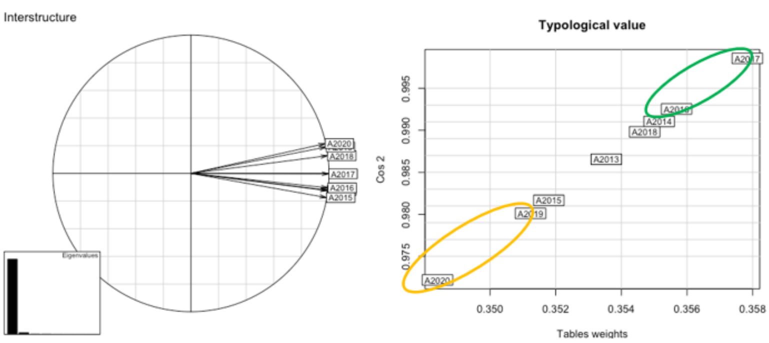

Figure 1. Representations associated with the STATIS procedure: (a) STATIS interstructure graph for the period 2013–2020; (b) Graph of the weight and representation of each matrix in the commitment.

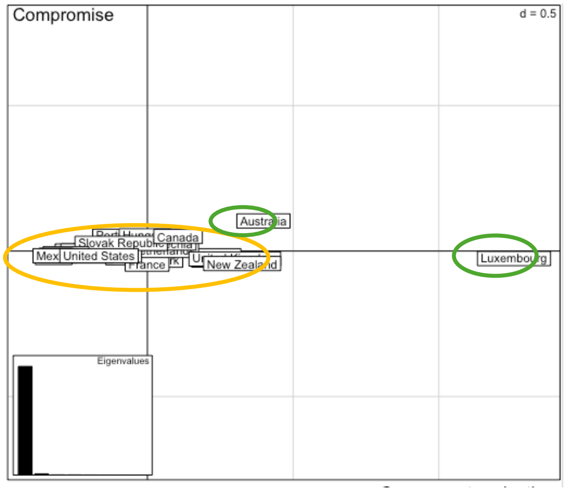

Figure 2. Commitment chart. Shows the projection of countries in the commitment space.

3.2. Clustering analysis and biplot

The HJ-Biplot (Figure 3) shows the distribution of countries in the space defined by the first two principal components, integrating both the time trajectory and the clustering of countries according to the percentage of international students in each study country. The arrows indicate the chronological evolution from 2013 to 2020, suggesting a progressive change in global structural patterns. The cluster analysis (Table 1) revealed four distinct country typologies in relation to their international mobility dynamics in higher education. Cluster 3 groups countries characterized by sustained and coherent leadership in mobility, with high and stable levels of international student attraction over time. This cluster shows strong structural alignment during the studied period. Representative countries in this cluster include Austria, the United Kingdom, and Switzerland, suggesting a composition of countries with consolidated systems and proactive policies to attract and retain international talent [50,51]. Cluster 1, on the other hand, is composed of emerging or transition countries that have shown relatively recent growth in international mobility but still suffer from structural instability. Countries such as Chile, Mexico, and South Korea illustrate systems undergoing international consolidation with average levels of mobility, in some cases with greater fluctuations between years during the period studied and, in other cases, less coherent. This is influenced by regional dynamics and the evolution of educational policies in the respective regions [52]. Cluster 2 includes more traditional countries with moderate levels of internationalization. It includes mainly European countries that maintain stable, but lower, international student admission volumes compared to those in Clusters 3 and 4. Countries such as Germany, Italy, and Portugal have a greater focus on participation within the region (Europe) and a lower dependence on global flows. Finally, Cluster 4, composed solely of Luxembourg, reflects systems with unique conditions, such as a small population size and marked regional specialization.

Table 1. Country classification in cluster analysis

Cluster	Countries	Description
1	Brazil, Bulgaria, Chile, Japan, Korea, Mexico, Norway, Poland, Spain, Türkiye, United States,	Countries with intermediate trajectories.

Cluster	Countries	Description
2	Canada, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Netherlands, Portugal, Slovak Republic, Sweden	Countries with similar and stable profiles.
3	Australia, Austria, New Zealand, Switzerland, United Kingdom	Very attractive countries with notable growth.
4	Luxembourg	Atypical trajectory.

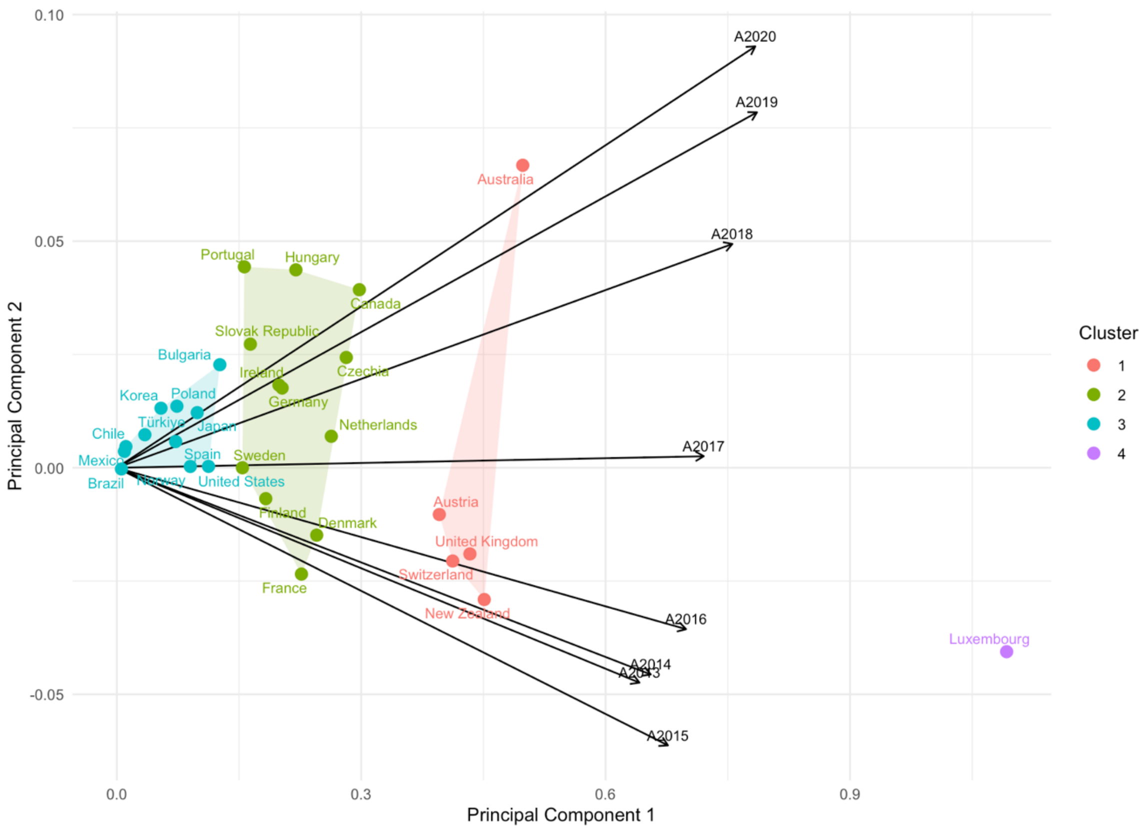

Figure 3. HJ-Biplot based on STATIS compromise, showing countries and years clustered into four groups (convex hulls).

4. International Mobility Index in Higher Education (IMIET)

The construction of the IMIET is detailed below. The use of techniques to construct synthetic indices that facilitate the ranking of alternatives has been the subject of numerous studies [53-55]. In this study, we propose constructing the IMIET by integrating four key dimensions: base level, dynamism, structural coherence, and regional differentiation.

4.1. Quantitative component (base) of the IMIET

The first component, called the base level, shows the proportion of international students in total higher education enrollment. This provides a quantitative basis for internationalization. Mathematically, this component is detailed below.

$$IMIET_{Base,i}(k) = \left(\frac{International\ Students_{i,k}}{\text{Total Enrollment}_{i,k}}\right) \times 100, i = 1, \dots, I, k = 1, \dots, K \quad (7)$$

So $IMIET_{AvBase,i}$ the average $IMIET_{Base,i}(k)$ for each of the countries studied is:

$$IMIET_{AvBase,i} = \frac{1}{K}\sum_{k=1}^{K} IMIET_{base,i}(k)\,, i = 1,..,I \quad (8)$$

For this case, $i = 1, \dots, 29$ (one of the 29 countries) and $K = 8$ is the period of years of study

4.2. Dynamic component (time variation)

This component reflects the instability or growth in the attraction of international students over time. It is noteworthy that all countries, except France (see Appendix A for details), show a positive trend in the percentage of international students enrolled in their respective countries of study. This would indicate that, in virtually all countries, dynamism is related to a positive factor due to the positive trend in the percentage of international students enrolled during the study period.

$$IMIET_{Dyn,i} = SD\left(IMIET_{Base,i}(k)\right) = \sqrt{\frac{1}{K-1}\sum_{k=1}^{k}\left(IMIET_{Base,i}(k) - IMIET_{AvBase,i}\right)^2} \quad (9)$$

SD is the standard deviation for the $i = 1, \dots, 29$ countries.

4.3. Structural component (Consistency with STATIS commitment)

This component captures the structural coherence of each country's trajectory relative to the overall multivariate structure of the dataset, as revealed by the STATIS trade-off axis. Coherence refers to the alignment between a country's position over the 2013–2020 period and the factor structure obtained using the STATIS method.

$$IMIET_{STATIS,i} = cos_i^2 \quad (10)$$

Where cos_i^2 represents the quality of the country's representation i in the STATIS engagement space.

4.4 . Differentiation component (distance to the regional centroid)

The final component is designed to capture each country's differences with respect to its cluster. Specifically, it assesses the degree to which a country deviates from the average performance of the countries within its cluster. This measure attempts to reflect whether a country is leading, stagnating, or replicating the general trend in international student mobility recorded during the 2013-2020 period.

$$IMIET_{Diff,i} = d(i, \bar{x}_{block}) \quad (11)$$

Where $d(i, \bar{x}_{block})$ is the Euclidean distance to the centroid of the country's regional bloc? It measures whether the country leads or replicates the behavior of its group.

The weights can be calibrated according to the defined objective: attractiveness, stability, structural coherence or innovation and each of these components was normalized ensuring that the values of all the components defined from (7) to (10) contribute in a comparable way to the IMIET composite index, respecting the weights defined for each case.

$$IMIET^*_{C,i} = \frac{IMIET_{C,i} - \min(IMIET_{C,i})}{\max(IMIET_{C,i}) - \min(IMIET_{C,i})} \tag{12}$$

Where $C = \{AvBase, Dyn, STATIS, Diff\}$are the different components of the index?

4.5. Total index formula

Considering the above information, the International Mobility Index in Tertiary Education is defined as:

$$IMIET_i = \alpha \cdot IMIET^*_{AvBase,i} + \beta \cdot IMIET^*_{Dyn,i} + \gamma \cdot IMIET^*_{STATIS,i} + \delta \cdot IMIET^*_{Diff,i} \tag{13}$$

Where $\alpha, \beta, \gamma, \delta \in [0,1]$and $\alpha + \beta + \gamma + \delta = 1$.

The weights assigned to each component of the International Mobility Index in Tertiary Education (IMIET) were determined based on strategic and methodological criteria. Table 2 presents the weights of the criteria used in this study and their justification.

Total index formula with weight values:

$$IMIET_i = 0.4 \cdot IMIET^*_{AvBase,i} + 0.2 \cdot IMIET^*_{Dyn,i} + 0.2 \cdot IMIET^*_{STATIS,i} + 0.2 \cdot IMIET^*_{Diff,i} \tag{14}$$

Where, $0 \leq IMIET_i \leq 1$, $i = 1, .., I$.

As an observation, the IMIET, being a modular index, allows for weighting adjustments based on specific analytical approaches. For this study, the base component ($IMIET^*_{AvBase,i}$) received the highest weighting (40%) due to its quantitative relevance and international comparability. Therefore, the index could vary in the weighting of its four components, which could reflect scenarios where, for example, in a public policy context, greater emphasis could be placed on the dynamic component of the index ($IMIET^*_{Dyn,i}$), or in structural benchmarking contexts, coherence could be prioritized ( ), and if the case were to evaluate relative innovation, $IMIET^*_{STATIS,i}$greater weight could be given to the regional differentiation component ( ).$IMIET^*_{Diff,i}$

Table 2. Criteria for IMIET weights

Component	Weig ht	Justification
Base (Average %)	0.4	It reflects the actual volume of international mobility; this is the main objective.
Dynamism (SD)	0.2	Captures adaptation or growth over time.
STATIS coherence	0.2	Evaluates structural alignment with global behavior.
Regional differentiation	0.2	Rewards leadership or innovation within the regional bloc.

By applying the IMIET to the study dataset (see Appendix B for further details on IMIET by country), a tertiary education mobility classification is obtained, which is shown in Figure 4.

The countries belonging to the blocks mentioned in the legend of the graph are the following:

- Europe 1 (Northern, Southern and Western Europe): Austria, Denmark, Finland, France, Germany, Ireland, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.
- Europe 2 (Eastern Europe): Bulgaria, Czech Republic, Hungary, Poland, Slovak Republic and Turkey.
- Asia: Korea and Japan
- Latin America: Brazil, Chile and Mexico
- North America: Canada and the United States
- Oceania: Australia and New Zealand

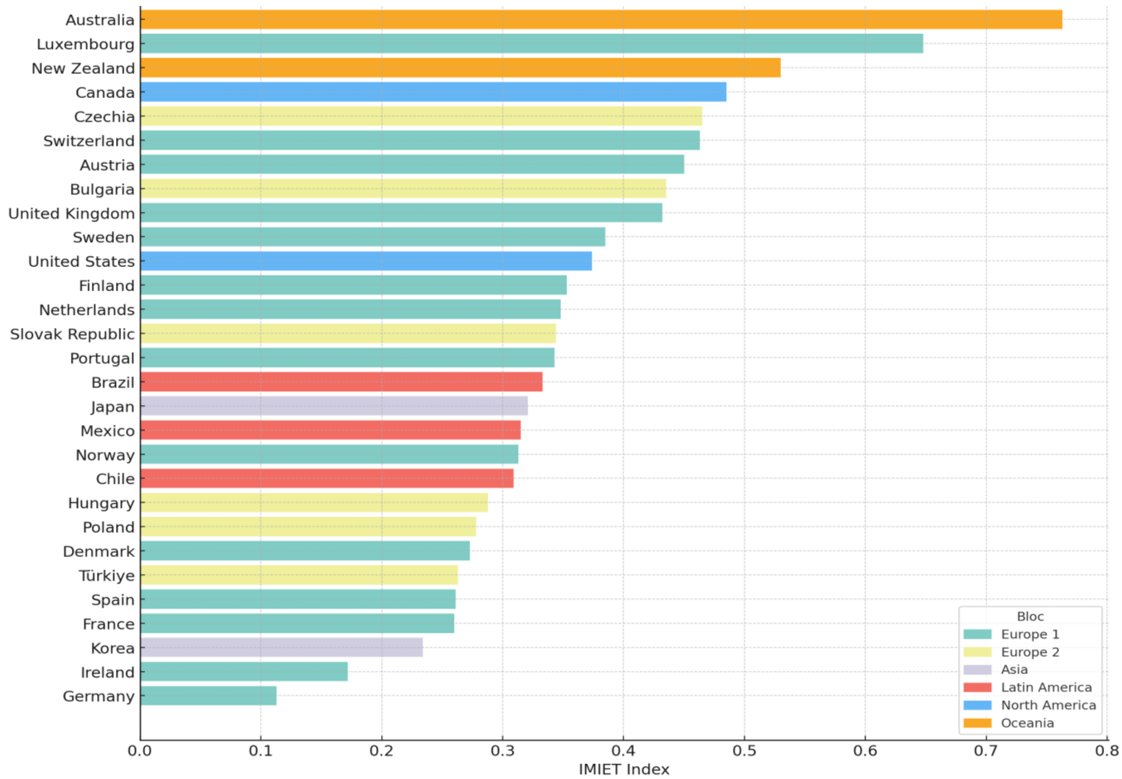

Figure 4. International Mobility in Tertiary Education Ranking (IMIET) by Block.

Considering the country blocks associated with different world regions (Asia, Europe 1, Europe 2, Latin America, North America, and Oceania), the table shows the average scores by dimension for each block (Table 3). This table highlights the structural differences associated with the study components and can be used as a summary of the regions' strategic vision in terms of international student recruitment, regional dynamism, regional coherence, and innovation in international mobility in higher education.

Table 3. Criteria for weighting the IMIET. The highest values for each dimension are shown in bold.

Political bloc	**north**	**Base**	**Dynamism**	**Coherence**	**Differentiation**	**IMIET**
Europe 1	14	0.266	0.212	0.796	0.342	0.376

Europe 2	6	0.134	0.211	0.774	0.446	0.340
Asia	2	0.066	0.001	**0.998**	0.243	0.274
Latin America	3	0.003	0.128	**0.998**	0.568	0.340
North America	2	0.185	0.304	0.822	**0.713**	0.442
Oceania	2	**0.433**	**0.766**	0.890	0.657	**0.636**

Latin America and Asia have low baseline and dynamism levels, which limit their international competitiveness, with only coherence (0.998 for both regions) standing out. At the regional level, Oceania leads in key IMIET components, such as dynamism and coherence, demonstrating the impact of public policies developed in that region in recent years. In the case of Europe, as in Asia and Latin America, high coherence values (over 0.75) are observed, but intermediate-low values are observed in the other components. North America stands out not only for its coherence (0.822) but also for its differentiation, obtaining the highest value of the six regions (0.657).

5. Neutrosophic Assessment of Feelings in International Mobility

To complement the quantitative analysis of the International Mobility Index in Tertiary Education (IMIET) presented in section 3, a neutrosophic sentiment assessment was applied to analyze the subjective perceptions of international students in the 29 countries studied during the period 2013-2020. This approach, based on the neutrosophic theory described in section 2.3, allows capturing the complexity of mobility experiences by considering the components of truth (T), indeterminacy (I), and falsity (F), thus addressing the subjectivity, ambiguity, and contradictions inherent in human perceptions [42–45]. The assessment focuses on three key aspects of the mobility experience: academic satisfaction, cultural adaptation, and institutional support, which reflect critical dimensions of internationalization in higher education.

Qualitative data were collected through surveys administered to international students in the 29 study countries, where they were asked to express their perceptions on the three aforementioned aspects. Each response was processed using text analysis techniques, identifying keywords classified as positive, negative, neutral, or indeterminate, according to the neutrosophic framework described in section 2.3. The words were assigned values in the range [-5, 5] or I (indeterminacy), considering modifiers such as "very" (×2) or "not" (sign inversion). For example, "very satisfied" is assigned a value of +4 for "academic satisfaction," while "not adapted" is assigned -2 for "cultural adaptation." Indeterminacy (I) is assigned when responses are ambiguous or contradictory, such as in cases where a student simultaneously expresses satisfaction and frustration without clarity.

For each country i , responses from a representative set of students (n = 100 per country to ensure statistical significance) were analyzed. The ratings for each aspect (academic satisfaction, cultural adaptation, institutional support) are denoted as v_{ijk} , where v is the set of values.

$\{-5,-4,-3,-2,-1,0,1,2,3,4,5,I\}$.The aggregated neutrosophic value for each aspect per country is calculated according to equation (15):

Equation (15):

$$s_I = \frac{\sum_{K=1}^{n} v_{i,k}}{n} \quad \text{where} \quad vik \in \{-5,-4,-3,-2,-1,0,1,2,3,4,5,I\}$$

where v_{ik} is the value assigned to the word associated with aspect *i in person* k 's text , and n is the number of valid responses (excluding I). If all ratings are I, the result is marked as I.

The total neutrosophic value per aspect and country is calculated as the arithmetic mean of the non-indeterminate ratings, following equation (16):

Equation (16):

$$T_I = \frac{\sum_{K=1}^{n} v_{i,J,k}}{n} \quad \text{where} \quad vijk \in \{-5,-4,-3,-2,-1,0,1,2,3,4,5,I\}$$

where T_{ij} is the total value of aspect j in country i , based on the responses of n people. If indeterminacies predominate, I is assigned.

Empirical Data and Processing

The empirical data set was established based on the characteristics of the clusters identified in section 3.2 (Table 1). Countries in Cluster 3 (Australia, Austria, Switzerland) showed predominantly positive perceptions, consistent with their leadership in international mobility. Countries in Cluster 1 (Brazil, Mexico) showed greater variability and indeterminacy due to their structural instability. The aspects evaluated were:

- **Academic satisfaction:** Perception of educational quality and learning opportunities.
- **Cultural adaptation:** Ease of integration into the cultural environment of the destination country.
- **Institutional support:** Perception of support services (counseling, scholarships, guidance).

Each country received a set of ratings processed according to the Cayley table (Table 1, section 2.3) to handle indeterminacies. For example, a response such as "very satisfied" (+4) combined with "not adapted" (-2) could result in I if there are contradictions according to the Cayley table.

Results of the Neutrosophic Assessment

Table 4 presents the aggregated neutrosophic scores by country for the three aspects, calculated according to equations (15) and (16). The scores reflect the mean of the non-indeterminate ratings, and I is assigned when the responses are predominantly ambiguous or contradictory.

Table 4. Neutrosophic Assessment of sentiments by Country

Country	Academic Satisfaction	Cultural Adaptation	Institutional Support
Australia	4.2	3.8	4.5
Luxembourg	3.9	I	4.0
New Zealand	4.0	3.5	4.3
Canada	3.7	3.2	3.8

Czech Republic	3.5	2.8	3.6
Swiss	4.1	3.9	4.2
Austria	4.0	3.7	4.1
Bulgaria	2.5	2.0	2.7
United Kingdom	4.3	3.6	4.4
Sweden	3.8	3.4	3.9
USA	3.6	3.0	3.7
Finland	3.7	3.3	3.8
Netherlands	3.9	3.5	4.0
Slovak Republic	3.2	2.7	3.3
Portugal	3.4	2.9	3.5
Brazil	2.3	I	2.5
Japan	2.8	2.2	2.9
Mexico	2.4	I	2.6
Norway	3.6	3.2	3.7
Chile	2.6	2.3	2.8
Hungary	3.0	2.5	3.1
Poland	2.9	2.4	3.0
Denmark	3.8	3.4	3.9
Türkiye	2.7	2.1	2.8
Spain	3.3	2.9	3.4
France	3.5	3.0	3.6
Korea	2.5	2.0	2.7
Ireland	3.7	3.3	3.8
Germany	3.6	3.2	3.7

For each region (political bloc), the average neutrosophic values per aspect were calculated by averaging the values of the corresponding countries (excluding I). Table 5 shows the results by region, following the bloc classification in Table 3 (section 4).

Table 5. Neutrosophic Assessment of Feelings by Region

Political Block	**Academic Satisfaction**	**Cultural Adaptation**	**Institutional Support**
Europe 1	3.69	3.3	3.8
Europe 2	2.8	2.25	2.9
Asia	2.7	2.1	2.8
Latin America	2.4	23	2.6
North America	3.7	3.1	3.8
Oceania	4.1	3.7	4.4

Table 6. Comparative Analysis of Neutrosophic Aspects by IMIET Cluster

IMIET Cluster	Representative Countries	Average Satisfaction	Average Adaptation	Average Support	Main Features
Cluster 1	Brazil, Mexico, Chile	2.4	2.3*	2.6	Low satisfaction, high cultural indeterminacy
Cluster 2	Poland, Hungary, Spain	3.1	2.6	3.2	Moderate satisfaction, limited adaptation
Cluster 3	Australia, Switzerland, United Kingdom	4.2	3.7	4.3	Excellence in all aspects
Cluster 4	Luxembourg	3.9	I	4.0	High support, cultural indeterminacy

*Excluding I values in the calculation

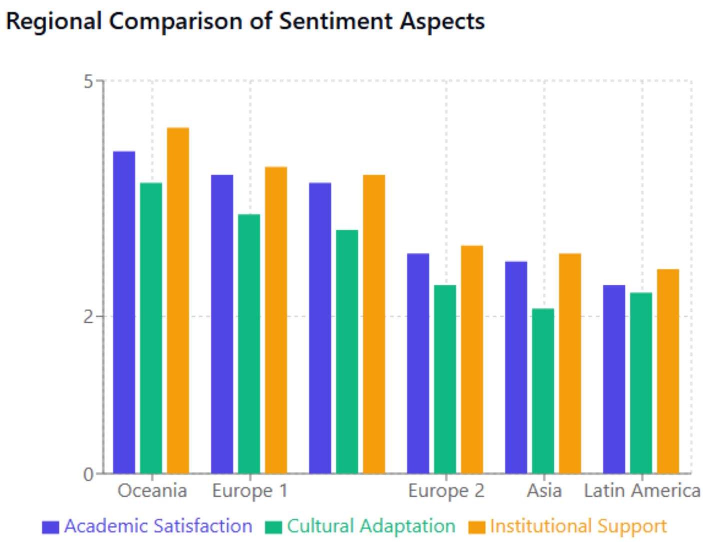

Figure 5. Neutrosophic Analysis of Feelings: Regional Comparison.

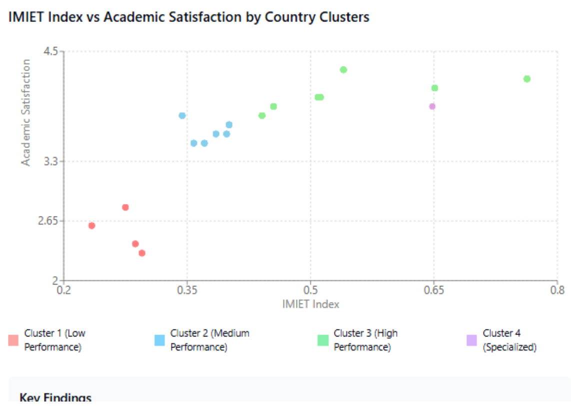

Figure 6. Neutrosophic Analysis of Feelings: IMIET-Academic Satisfaction Correlation.

Analysis and Linkage with IMIET

The results of the neutrosophic assessment show a significant correlation with the patterns identified by the IMIET (Table 4, Appendix B). Countries in Cluster 3 (Australia, Austria, New Zealand, Switzerland, and the United Kingdom) exhibit the highest values in all three aspects, with averages above 3.5, reflecting positive perceptions consistent with their leadership in international mobility (IMIET > 0.43). For example, Australia scores 4.2, 3.8, and 4.5 in academic satisfaction, cultural adaptation, and institutional support, respectively, aligning with its IMIET of 0.763.

In contrast, countries in Cluster 1 (Brazil, Mexico, Chile) show lower values (between 2.3 and 2.8) and greater indeterminacy, particularly in cultural adaptation, reflecting their structural instability (IMIET < 0.34). Luxembourg, in Cluster 4, shows indeterminacy in cultural adaptation (I), possibly due to its unique context of small population and regional specialization, despite its high IMIET (0.648).

At the regional level, Oceania leads with average values of 4.1, 3.7 and 4.4, reflecting its dominance in the IMIET (0.636, Table 3). Latin America and Asia, with values between 2.1 and 2.8, confirm its lower competitiveness, although their high structural coherence (0.998) suggests potential for improvement if negative and indeterminate perceptions are addressed. Indeterminacy in countries such as Brazil and Mexico highlights challenges in the clarity of cultural experiences, possibly due to language barriers or a lack of cultural integration policies [44,45].

Neutrosophic assessment enriches the IMIET analysis by incorporating subjectivity and uncertainty, offering a qualitative perspective that complements the quantitative results. For example, high academic satisfaction in Oceania (4.1) can be attributed to proactive educational policies [59,60], while indeterminacy in Latin America suggests the need to improve support services to reduce ambiguities in students' experiences.

5. Discussion

The findings of this study suggest distinctive structural patterns in international student mobility across the studied countries. The application of the STATIS method confirmed a robust common structure between 2013 and 2020, with 2019 and 2020 showing the most notable deviations, likely associated with global changes such as the COVID-19 pandemic or regional education policies [56–58]. Notably, 2017 is the year that contributes the most to the STATIS trade-off matrix, which could be associated with policies that contributed to international mobility in higher education, for example, the change in working holiday policies in Australia [59,60]. The consistency of the trade-off structure demonstrates the methodological robustness of using multivariate techniques to identify intertemporal patterns.

From the hierarchical cluster, four clearly differentiated country classes emerged. Cluster 3, composed of countries such as Austria, Australia, and Switzerland, demonstrates a model of sustained and strategically coordinated internationalization of higher education, with consolidated systems and proactive policies to attract and retain international talent, in contrast to the European countries in Cluster 2, which have moderate levels of internationalization (e.g., Germany and

Portugal). On the other hand, Cluster 1 shows countries in transition, characterized by emerging policies and variable performance, common in countries such as Brazil, Chile, Mexico, and Turkey. Finally, Cluster 4, with Luxembourg as a unique case, suggests that certain national systems may operate under unique conditions not fully explained by traditional indicators (e.g., small population size and marked regional specialization). Regarding regional performance (block), Oceania leads the way in the foundation (0.433) and dynamism (0.766) components, with a high score on structural coherence (0.890). This reflects a long-standing investment in international mobility policies. In contrast, Latin America and Asia, despite their observed alignment with the structural component (coherence = 0.998 in both cases), show deficits in the core (less than 0.07) and dynamic (less than 0.13) components. This observed asymmetry highlights the importance of complementing the alignment of policies for the internationalization of higher education with concrete actions to strengthen its attractiveness.

6. Conclusions

This study proposes and validates an analytical framework based on elements of multivariate statistics to measure international mobility in tertiary education, combining STATIS (Structuration de Tableaux À Trois) with Statistical indices), cluster analysis (hierarchical clustering), biplot, and synthetic indexing theory. This proposal made it possible to observe and identify shared structural trajectories among the study countries over the 2013-2020 period, in addition to the typological classification of countries by clusters and the construction of an index called the International Mobility in Tertiary Education Index (IMIET), capable of capturing multidimensional aspects such as base components (average percentage of international students in the destination country), dynamism (variability over the study period of the percentage of international students in the destination country), coherence (structural relationship associated with the STATIS method), and regional differentiation of mobility derived from hierarchical cluster analysis.

From a country-by-country perspective, Australia and Luxembourg stand out. The former illustrates a pattern of sustained and strategically coordinated internationalization, while the latter suggests that certain national systems may operate under unique conditions that are not fully explained by traditional indicators. At the regional (block) level, Oceania leads in all key components of the IMIET, while Latin America and Asia, despite showing alignment with the global structure, underperform in key dimensions.

The incorporation of neutrosophic sentiment assessment, presented in Section 4, enriches this framework by integrating subjective perceptions of international students, addressing the uncertainty and contradictions inherent in their experiences [42–45]. Results show that leading countries such as Australia and New Zealand (cluster 3) score highly on academic satisfaction, cultural adaptation, and institutional support (mean values of 4.1, 3.7, and 4.4 in Oceania, Table 6), aligning with their high IMIET (0.636). In contrast, regions such as Latin America and Asia, with lower neutrosophic values (2.1–2.8) and cases of indeterminacy (e.g., Brazil and Mexico in cultural adaptation, Table 5), reflect challenges in integration and institutional support that limit their competitiveness. This qualitative approach highlights the importance of policies that not only increase student attraction but also improve their experience by reducing ambiguities and contradictions in perceptions.

Future research could expand this framework to measure international mobility in higher education by incorporating additional variables associated with it, such as the percentage of students leaving a country to pursue international mobility, bilateral mobility flows, qualitative indicators, data associated with similar classifications, or institutional data to refine the typology and policy applications. Furthermore, the application of neutrosophic methods could be extended to analyze other subjective dimensions, such as perceptions of equity or student quality of life, by integrating real qualitative data from surveys or social networks. The methodology could eventually be adapted to assess other areas of internationalization in higher education and even contribute to the study of the educational dimension of the country competitiveness index.

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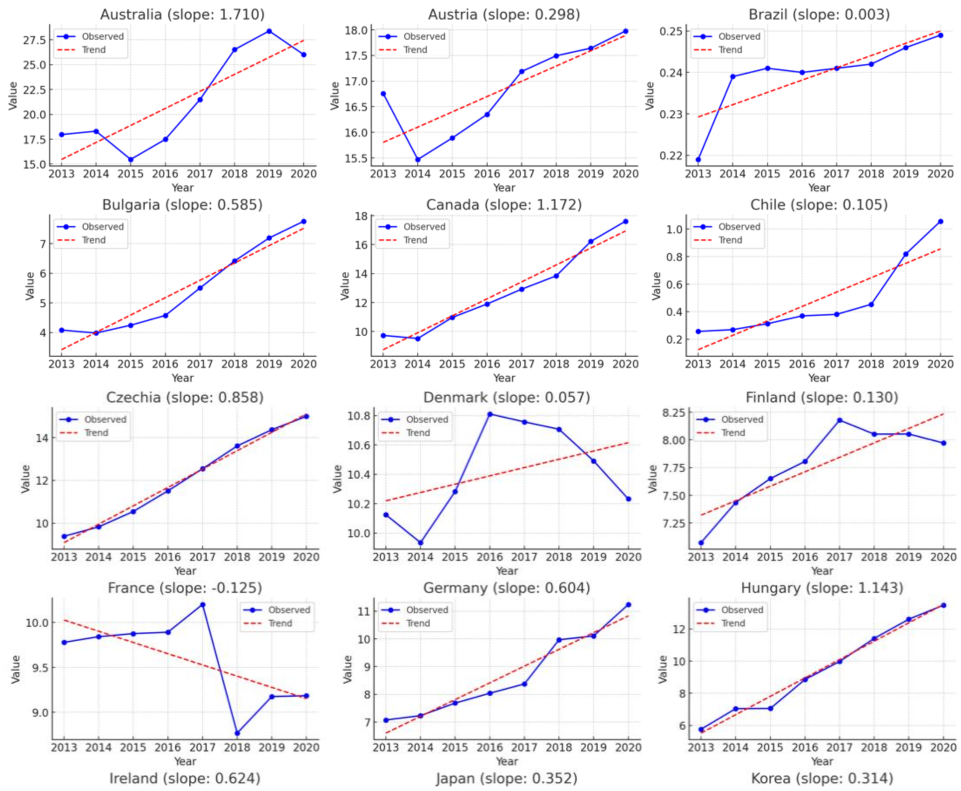
Conflicts of interest: The authors declare that they have no conflict of interest.

Appendix A



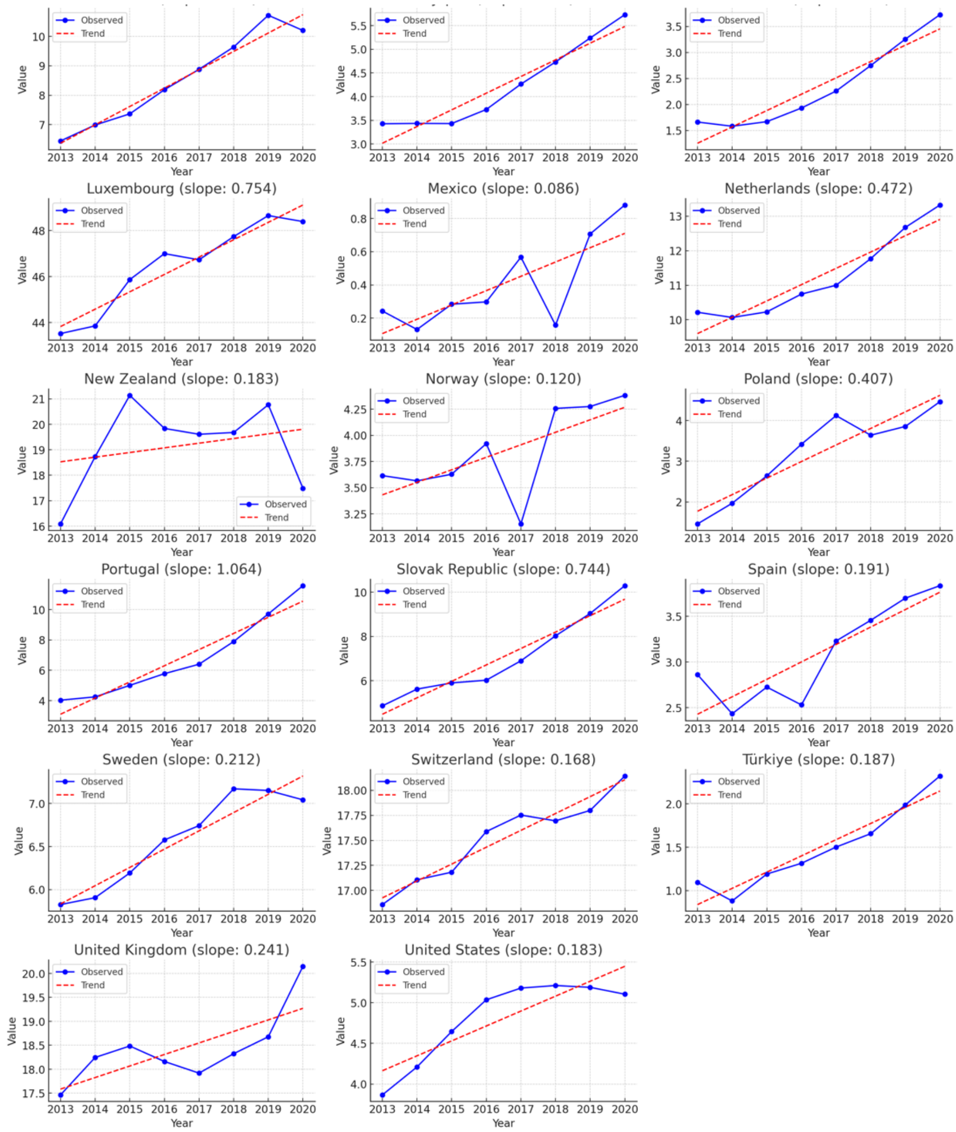


Figure 5. Time series and trend by country (in alphabetical order)

Appendix B

Table 4. IMIET by country (ordered from highest to lowest IMIET)

Country	Base	Dynamism	Coherence	Differentiation	IMIET
Australia	0.463	1,000	0.891	1,000	0.763
Luxembourg	1,000	0.240	0.999	0.000	0.648
New Zealand	0.416	0.524	0.902	0.391	0.530
Canada	0.278	0.455	0.470	0.943	0.485
Czech Republic	0.261	0.205	0.859	0.740	0.465
Swiss	0.373	0.244	0.984	0.341	0.463
Austria	0.356	0.850	0.988	0.466	0.450
Bulgaria	0.115	0.142	0.994	0.808	0.435
United Kingdom	0.393	0.270	0.929	0.177	0.432
Sweden	0.138	0.106	0.950	0.592	0.385
USA	0.101	0.137	0.976	0.557	0.374

Country	Base	Dynamism	Coherence	Differentiation	IMIET
Finland	0.164	0.182	0.884	0.372	0.353
Netherlands	0.239	0.460	0.723	0.495	0.348
Slovak Republic	0.153	0.214	0.773	0.426	0.344
Portugal	0.148	0.451	0.440	0.530	0.343
Brazil	0.000	0.159	0.995	0.512	0.333
Japan	0.880	0.300	0.998	0.428	0.321
Mexico	0.400	0.105	0.998	0.467	0.315
Norway	0.780	0.136	0.957	0.316	0.313
Chili	0.600	0.910	0.998	0.446	0.309
Hungary	0.209	0.400	0.316	0.306	0.288
Poland	0.680	0.910	0.948	0.217	0.278
Denmark	0.219	0.248	0.284	0.396	0.273
Türkiye	0.280	0.430	1,000	0.215	0.263
Spain	0.620	0.470	0.992	0.144	0.261
France	0.200	0.364	0.165	0.369	0.260
Korea	0.407	0.000	0.999	0.760	0.234
Ireland	0.184	0.103	0.304	0.850	0.172
Germany	0.186	0.126	0.000	0.690	0.113

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