

Article

Neural STATIS: A Nonlinear Multiblock Consensus Framework via Learned Latent Representations

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Abstract

Multivariate analysis of multi-table databases presents significant challenges when underlying structures exhibit nonlinear and time-varying behavior, limiting the applicability of classical linear methods such as STATIS. This study introduces Neural STATIS, a novel methodological approach that integrates the representational capacity of neural networks with the structural logic of classical STATIS to capture nonlinear dependencies across multiple data tables. Longitudinal OECD data encompassing socioeconomic and sustainable development variables across multiple time intervals were used to evaluate the method's feasibility and enable direct comparison with traditional STATIS. Neural STATIS successfully identified complex trajectories and subtle temporal patterns that classical linear analysis failed to detect, providing deeper visualization of dynamic relationships across tables. These findings demonstrate that Neural STATIS offers a more adaptive and comprehensive analytical framework than conventional linear methods, particularly in contexts characterized by ambiguity and nonlinearity. Grounded in Neutrosophic philosophy, which explicitly acknowledges uncertainty as an inherent component of complex phenomena, this approach broadens the scope of multi-table analysis and facilitates more informed decision-making in real-world settings where linearity assumptions are not sustainable.

Keywords: neural networks; OECD; multi-table analysis; Neural STATIS; nonlinear learning; longitudinal data; neutrosophy



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1. Introduction

Interpreting complex phenomena across social, economic, technological, and environmental domains requires the simultaneous analysis of multiple data tables through multivariate statistical methods. In such settings, observations are rarely governed by linear relationships; instead, they exhibit intricate dependencies, non-trivial interactions, and evolutionary trajectories that conventional analytical perspectives are ill-equipped to describe. Identifying consistent structural patterns, advancing scientific understanding, and supporting decision-making under uncertainty all depend on the capacity to model relationships across tables that may represent nations, populations, or time periods—a challenge that motivates the development of more expressive analytical frameworks.

The field of multi-table analysis has progressed substantially from early exploratory techniques toward increasingly sophisticated methods. Among the most influential contributions is STATIS (*Structuration des Tableaux à Trois Indices de la Statistique*) [1–4], a method widely adopted for its ability to compare and synthesize information from multiple data matrices, systematically characterizing areas of agreement and disagreement across them [5,6]. Over time, STATIS has been extended and adapted for various structured data settings, establishing itself as a reference framework in multivariate analysis. Nevertheless, a fundamental limitation persists: STATIS relies exclusively on linear operators, and this mathematical constraint restricts its capacity to represent nonlinear dependencies [7,8]—a phenomenon that is not exceptional but rather pervasive across real-world complex systems. When nonlinearity is ignored, the resulting low-dimensional representations may suppress relevant latent structure and lead to incomplete or biased conclusions, particularly in datasets whose geometry cannot be adequately described by linear projections.

This tension between the assumptions of classical multi-table methods and the intrinsic complexity of empirical data is not merely technical; it reflects a broader divergence in the field between parsimony-oriented linear approaches and the growing recognition that real systems require flexible, nonlinear representations. The need for such representations has been independently reinforced in adjacent domains: hybrid deep learning architectures that integrate adaptive feature extraction and temporal correlation modeling have been shown to outperform conventional methods in demanding analytical environments [9], and evidence from large-scale applied studies confirms that matching the modeling strategy to the structural characteristics of the data is critical for reliable inference [10]. These converging findings underscore that linearity is not a neutral assumption—it is a hypothesis that, when violated, carries substantive analytical costs.

The present work seeks to resolve precisely this discrepancy. The central research question addressed here is: *How can an analytical framework characterize the co-evolution of data from multiple tables when the relationships among variables are not strictly linear?*

To address this question, we introduce Neural STATIS, a nonlinear extension of the STATIS framework that integrates the structural logic of multi-table analysis with the representational capacity of neural networks [11,12]. This approach preserves the core philosophy of STATIS—identifying consensus structures across tables and situating individual tables relative to that consensus—while extending it through learned nonlinear mappings capable of capturing complex latent spaces and dynamic trajectories that remain hidden under linear assumptions.

The specific objectives of this work are: (i) to develop and formalize Neural STATIS as a nonlinear extension for multi-table data analysis; (ii) to validate the method using a real-world case study based on OECD socioeconomic and sustainability indicators across multiple time periods; (iii) to compare results with classical STATIS and identify structural patterns that the nonlinear approach uniquely reveals; and (iv) to discuss the theoretical and practical implications of Neural STATIS for multivariate research and complex data-driven decision-making. The results demonstrate that Neural STATIS recovers nonlinear structure that the linear framework systematically suppresses, offering a more faithful representation of the trajectories embedded in heterogeneous socioeconomic data and broadening the analytical scope of multi-table methods.

2. Materials and Methods

2.1. Introduction to the STATIS Approach

The STATIS method is a multivariate analysis technique for the simultaneous analysis of multiple datasets; it is known by its abbreviation ACT (Analyze Common Tables). The central idea is that all datasets are evaluated using the same units of observation. This

method facilitates the detection of common patterns by constructing a matrix called a “commitment.” Based on a criterion aimed at optimizing the consistency between different data segments, this commitment acts as an operator that synthesizes the information from these blocks in the most efficient way possible.

This method is developed in three main stages that follow one another. Initially, during the interstructure phase, metrics such as RV coefficients are used to assess the affinity between the different datasets. The commitment stage, following synthesis, involves integrating the common structure of all tables into a single shared table operator. In the Intrastructure phase, the observations from each individual table are finally projected onto the shared area recognized by the commitment, making possible a collaborative visualization and analysis.

This procedure is useful for comparing multidimensional data originating from multiple sources or times. It is based on the Hilbert-Schmidt dot product [11,13–20], a mathematical tool used to measure similarities between matrices or operators, and on Euclidean concepts (classical geometry). Its guarantee is the geometric rigidity between blocks (data structures that do not deform when compared, maintaining their mathematical form) and multivariate readability (meaning that the results are interpretable when analyzing several variables simultaneously). We suggest reading Vivien and Sabatier’s work [21] for a comprehensive review and its extensions to more intricate systems.

2.1.1. Mathematical Basis of STATIS

The DO-ACT method is an extension of the STATIS-ACT approach, aimed at the comparative analysis of two data sets organized in multiple data tables (designated as $T_1 = \{X_k\}_{k=1}^{K_1}$ and $T_2 = \{Y_l\}_{l=1}^{K_2}$), which have been obtained from the same observations [22].

Definition of Blocks

This is based on two sets of matrices that, while it is essential that they share the same number of rows n (observations), may differ in the number of columns x (variables).

- Block set

$$X_k \in R^{n \times p_k}, \text{ for } k = 1, \dots, K_1$$

$$Y_l \in R^{n \times q_l}, \text{ for } l = 1, \dots, K_2$$

- Calculation of the block scalar product matrices

For each individual data block, its corresponding dot product matrix is determined, which represents a generalized covariance.

$$\text{For } X: W_k^X = X_k Q_k^X X_k^\top$$

$$\text{For } Y: W_l^Y = Y_l Q_l^Y Y_l^\top$$

In these expressions Q_k^X and Q_l^Y represent weighting matrices of the variables (Weight), which can be the identity matrix or normalization metrics such as Euclidean or Mahalanobis [12].

- Construction of the partial commitment of the first set of blocks

A “partial commitment” is established for each of the block sets; each commitment being defined as a weighted linear combination of their dot product matrices.

Commitment to:

$$T1: W_{comp}^X = \sum_{k=1}^{K_1} \alpha_k W_k^X$$

$$T2: W_{comp}^Y = \sum_{l=1}^{K_2} \beta_l W_l^Y$$

The weighting coefficients α_k and β_l , are typically determined by a preliminary STATIS analysis on each set separately.

- Obtaining Double Commitment (DO-ACT)

The fundamental concept of DO-ACT is the consolidation of the two partial commitments into a single matrix; the mathematical expression is:

$$W^{DO} = \frac{1}{2} (W_{comp}^X + W_{comp}^Y) \quad (1)$$

This matrix is calculated by averaging the two matrices, resulting in a double-compromise analysis, creating a balanced balance between the variability structure of both sets.

- Spectral analysis of DO commitment

A principal component analysis (PCA) is performed on the average double commitment matrix W^{DO} . This matrix is decomposed spectrally, as shown in the mathematical expression:

$$W^{DO} = U \Lambda U^\top \quad (2)$$

Λ (inertia explained) contains the eigenvalues.

U (principal components) are the eigenvectors.

Based on these results, the coordinates of the observations (F) in said common space of the individuals are calculated as:

$$F = U \Lambda^{1/2} \quad (3)$$

2.2. The Neural STATIS Method (Foundation and Procedure)

The Neural STATIS method follows the sequence shown below:

Autoencoder architecture and training details, the encoder f_θ is implemented as a symmetric autoencoder with architecture Input (10) $\rightarrow$ Dense (16, ReLU) $\rightarrow$ Z (5, linear) $\rightarrow$ Dense (16, ReLU) $\rightarrow$ Output (10), trained with Adam optimizer (learning rate = 0.001), MSE loss, batch size = 32, maximum 200 epochs, validation split = 0.15, and early stopping with patience = 20. Reproducibility is ensured via seed = 123 and TF_DETERMINISTIC_OPS = 1. Applied to the OECD panel ($n = 17$ countries, $K = 49$ years, $p = 10$ variables, 833 total observations, 1975–2023), the autoencoder achieved val_MSE = 0.027849, stopping at epoch 167. The hyperparameter λ in the compound loss (Equation (11)) was set via the Power-STATIS tuning procedure with Softmax parameterization ($\tau = 0.05$). To prevent variance dispersing into secondary axes, a spectral constraint $\lambda_2/\lambda_1 \leq \tau$ ($\tau = 0.08$) is imposed on the consensus eigenspace, concentrating representational capacity on the primary dimension.

2.2.1. Step 0: Statement and Notation

Let be a set of K tables $Y^{(Y)}$ with identical individuals (rows) and the same variables (columns), e.g., countries by indicators over several periods (OECD). We will assume each $X^{(k)}$ to be row/column centered and, if appropriate, standardized (consistent with classic STATIS; cf. [2,11,12]).

Classic STATIS works with linear operators (matrices of dot products and RV coefficients) to construct the commitment. Here, we propose replacing the linear component with nonlinear latent representations learned with neural networks [6,14], preserving the interstructure $\rightarrow$ commitment $\rightarrow$ projections philosophy [4,13,23].

2.2.2. Step 1: Nonlinear Representation Layer (Encoder)

We define an encoder $f_\theta : R^p \rightarrow R^q$ (MLP/autoencoder) divided between tables; for individual i in the same table k , this is the insertion of the neural network,

$$z_i^{(k)} = f_\theta(x_{i\bullet}^{(k)}) \in R^{n \times q} \quad (4)$$

$$Z^{(k)} = [(z_1^{(k)})^\dagger : (z_n^{(k)})^\dagger] \in R^{n \times q} \quad (5)$$

After obtaining the latent representations $Z^{(k)} \in R^{n \times q}$ using the autoencoder ε , the centered Gram matrix is constructed for each block k as:

$$G^{(k)} = H_n Z^{(k)} (Z^{(k)})^T H_n \quad (6)$$

where $H_n = I_n - \frac{1}{n} \mathbf{1}_n \mathbf{1}_n^T$ is the centering matrix; with this step, it is ensured that the similarities between blocks depend only on the relational restructuring between individuals, preserving the geometric invariance of the classic STATIS method; in other words, if f_θ were linear, $G^{(k)}$ would fall into the classic environment (ACT/STATIS; [12]), ensuring backward compatibility with STATIS.

2.2.3. Step 2: Neural Interstructure (Similarities Between Tables)

The similarity between two tables k and ℓ is defined by a nonlinear RV as the matrix cosine between centered Gram matrices:

$$\tilde{G}^{(k)} = H G^{(k)} H, \quad H = I_n - \frac{1}{n} \mathbf{1} \mathbf{1}^T \quad (7)$$

$$V_{NL}(G^{(k)}, G^{(l)}) = \frac{\langle \tilde{G}^{(k)}, \tilde{G}^{(l)} \rangle_F}{\|\tilde{G}^{(k)}\|_F \|\tilde{G}^{(l)}\|_F}, \text{ with } \langle A, B \rangle_F = \text{tr}(A^T B) \quad (8)$$

This creates the similarity matrix $S \in R^{k \times k}$ with entries $S_{kl} = RV_{NL}(G^{(k)}, G^{(l)})$, which works in a way analogous to the interstructure of STATIS [2,10]. The Frobenius normalization ensures that larger-scale blocks (i.e., due to latent dimensions with higher variance) do not artificially dominate the similarity matrix S . This practice is analogous to the trace normalization in classical STATIS [11,24–26] and ensures that $S_{k\ell} \in [-1, 1]$, with $S_{kk} = 1$.

2.2.4. Proposition 1—Linear Equivalence

If f_θ is linear and $Z^{(k)} = X^{(k)} W$ for some W , then RV_{NL} coincides with a classical RV between dot products of $X^{(k)}$. As a simple proof, substituting $G^{(k)} = X^{(k)} W W^T (x^{(k)})^T$ and using Frobenius cosine invariance under common positive scaling gives the classical appearance: $RV(X^{(k)} (x^{(k)})^T, X^{(l)} (x^{(l)})^T)$ [12].

2.2.5. Step 3: Neural Commitment as an Optimization Problem

A commitment G^C is sought that summarizes the K tables in the latent space:

$$G^C = \sum_{k=1}^K \alpha_k \tilde{G}^{(k)}, \quad \alpha_k \geq 0 \text{ and } \sum_k \alpha_k = 1 \quad (9)$$

The weights α are learned by maximizing global consistency:

$$\max_{\alpha \in \Delta^{K-1}} \phi(\alpha) = \sum_{k=1}^K RV_{NL}(G^C(\alpha), \tilde{G}^{(k)}), \quad \Delta^{K-1} = \{\alpha \geq 0, \sum \alpha_k = 1\} \quad (10)$$

What is shown in this section is a nonlinear analogue of the origin-interstructure problem in Stasis/ACT [1,11], where the first eigenvector provides the α . This is solved by a soft optimization concept such as projection onto the simplex or Softmax parameterization.

2.2.6. Proposition 2—Existence

ϕ is continuous and Δ^{K-1} is compact $\rightarrow$ there exists at least one global optimum α^* . If this is applied to a simulated environment, it would be Compactness + continuity (Weierstrass), and the continuity of RV_{NL} follows from the continuity of $\langle \cdot, \cdot \rangle_F$ and norms.

2.2.7. Step 4: Joint Training (f_θ and α)

Based on the literature review, “end-to-end” training is proposed, minimizing a compound loss:

$$Y = \underbrace{\frac{1}{K} \sum_{k=1}^K \|X^{(k)} - D(\varepsilon(X^{(k)}))\|_F^2}_{\text{reconstruction}} + \lambda \sum_{k=1}^K \alpha_k \|G_c - \underbrace{\tilde{G}^{(k)}}_{\text{consistency of commitment}}\|_F^2 \quad (11)$$

where $G_c = \sum_{j=1}^K \alpha_j \tilde{G}^{(j)}$ is the commitment matrix. The second component penalizes the discrepancy between each block and the global consensus, weighted by the weights α_k . The hyperparameter $\lambda > 0$ fully balances the reconstruction and the linearity of consensus, which is an idea related to non-linear multi-table integrations [24]. The consistency section forces the representations of all tables to look towards a common commitment as in the STATIS methodology.

2.2.8. Proposition 3—Consistency Towards the Linear Case

If l_{AE} forces f_θ to be linear and $\lambda \rightarrow \infty$, the optimum pushes G^C to align with the linear combination that maximizes the sum of RVs, reproducing the classical compromise. If this were put into a simulated space, it would be that in the limit the coherence term dominates; the problem reduces to maximizing a quadratic aspect in α equivalent to the first eigenvector of S [12].

2.2.9. Step 5: Consensus Space and Factorial Coordinates

At the moment when (θ, α) has been optimized, the trade-off is diagonalized:

$$G^C = U \Lambda U^T, \quad U^T U = I. \quad (12)$$

Therefore, the consensus factor coordinates of individuals are:

$$F = U \Lambda^{1/2} \in R^n \times r \quad (13)$$

With R dimensions retained, which are the inertia criteria, which can be evidenced in standard practices in STATIS and AFM [5,12].

2.2.10. Step 6: Projection of Each Trajectory Table

For each table k , a map projected on the consensus base is obtained; this yields two options:

Option A (geometric): “Gram biplot” type coordinates:

$$F^{(k)} = \check{G}^{(k)} U \Lambda^{-1/2} \quad (14)$$

Option B (Neural): Pass $X^{(k)}$ through the encoder and align:

$$F^{(k)} = Z^{(k)}R, R = \arg \min R \|Z^{(k)}R - F\|_F^2 \quad (15)$$

With orthogonal R to compare trajectories in the common space, the time trajectory of the same individual is obtained by joining the points $F_i^{(1)}, F_i^{(2)}, \dots, F_i^{(k)}$ [27–29].

2.2.11. Step 7: Variable Weighting and Interpretation

This step is described to interpret the variables in the consensus, using network sensitivities through classical gradients or loads if a linear bottleneck was used at the end of the encoder:

$$Saliencia_j = \frac{1}{K} \sum_k \left\| \frac{\partial Z^{(k)}}{\partial x_j} \right\|_F, (o) \text{ Cargas} = \text{corr}(X_{\bullet j}^{(k)}, F) \quad (16)$$

This section connects traditional multivariate reading such as eigenvalues and loads with explanations in non-linear models [27].

The complete pipeline of the proposed method is summarized in Algorithm 1.

Algorithm 1. Neural STATIS Framework

Line	Procedure
1	Step 1: Nonlinear Representation Layer (Encoder Integration)
2	For each table $k = 1, \dots, K$:
3	Pass individual rows through the encoder:
4	$z_i^{(k)} = f\theta(x_i \bullet^{(k)}) \in \mathbb{R}^p$
5	Construct the latent table matrix:
6	$Z^{(k)} = [z_1^{(k)}, \dots, z_n^{(k)}]^T \in \mathbb{R}^{n \times p}$
7	Compute the centered nonlinear Gram matrix:
8	$G^{(k)} = H_n Z^{(k)}(Z^{(k)})^T H_n$, where $H_n = I_n - (1/n)1_n 1_n^T$
9	Step 2: Neural Interstructure Mapping
10	Initialize similarity matrix $S \in \mathbb{R}^{K \times K}$.
11	For $k = 1, \dots, K$:
12	For $\ell = 1, \dots, K$:
13	Compute the nonlinear Escoufier RV coefficient (matrix cosine via Frobenius norm):
14	$S_{k\ell} = \text{RVNL}(G^{(k)}, G^{(\ell)}) = \langle G^{(k)}, G^{(\ell)} \rangle_F / (\ G^{(k)}\ _F \ G^{(\ell)}\ _F)$
15	Steps 3 and 4: Joint Optimization (End-to-End Training)
16	Initialize network weights θ and simplex commitment weights $\alpha \in \Delta^{K-1}$.
17	While not converged and epoch ≤ 200 :
18	Compute the neural commitment matrix:
19	$GC(\alpha) = \sum_{j=1}^K \alpha_j G^{(j)}$
20	Calculate the total loss function:

Algorithm 1. Cont.	
21	$L(\theta, \alpha) = (1/K) \sum_{k=1}^K \ X^{(k)} - D(f\theta(X^{(k)}))\ _F^2 + \lambda \sum_{k=1}^K \alpha_k \ GC(\alpha) - G^{(k)}\ _F^2$
22	Enforce the spectral constraint on the consensus eigenspace:
23	$\lambda_2/\lambda_1 \leq \tau$
24	Update parameters (θ, α) using the Adam optimizer.
25	If validation loss does not decrease for 20 epochs:
26	Terminate training (early stopping) and restore the best weights.
27	Step 5: Consensus Factorial Space Generation
28	Perform spectral decomposition on the optimal compromise:
29	$GC = U\Lambda U^T$
30	Calculate consensus individual coordinates:
31	$F = U\Lambda^{1/2} \in \mathbb{R}^{n_{xr}}$
32	Step 6: Trajectory Projections (Intra-structure Analysis)
33	For each table $k = 1, \dots, K$:
34	Align latent matrices to the consensus:
35	$R^{(k)} = \arg \min_R \ Z^{(k)}R - F\ _F^2$, subject to $R^T R = I$
36	Compute partial trajectory maps:
37	$F^{(k)} = Z^{(k)}R^{(k)}$
38	Step 7: Variable Saliency and Sensitivity Assessment
39	Compute structural loads and network sensitivities for interpretation:
40	$Saliency_j = (1/K) \sum_{k=1}^K \ \partial Z^{(k)} / \partial x_{\bullet j}\ _F$
41	or
42	$Loadings = \text{corr}(X_{\bullet j}^{(k)}, F)$

3. Results

To illustrate the application of the Neural STATIS method, an OECD panel of data composed of $K = 49$ years (1975–2023), $n = 17$ countries, and $p = 10$ socioeconomic and sustainability indicators was analyzed. The variables used, identified by their short codes, are detailed in Table 1. The analysis sought to capture the dynamic evolution of consensus structures across countries over time, revealing nonlinear patterns invisible to classic STATIS.

Quantitative evaluation and comparison with alternative methods

The Supplementary Report (Table 1) for Neural STATIS against benchmark methods on the same OECD dataset (standardized, $q = 5$ components): Neural STATIS Autoencoder: MSE = 0.1815, RMSE = 0.4261; Kernel PCA (RBF, $q = 5$): MSE = 0.3536, RMSE = 0.5946; Linear PCA ($q = 5$): MSE = 0.0676, RMSE = 0.2601. Neural STATIS outperforms Kernel PCA by 49% in reconstruction MSE.

Linear PCA achieves the lowest reconstruction error by design—it minimizes MSE as its objective—but captures only linear variance structure, precisely the limitation Neural STATIS is designed to overcome. Regarding data sufficiency: with 833 observations and $p = 10$ variables, the autoencoder operates in a low-dimensional regime.

Table 1. Supplementary report: neural network reproducibility & rigor.

Method Name:	Neural STATIS
Data Structure:	49 Tables (Years/Blocks)
Processing Mode:	Classic
Total Sample Points (N_tot):	833 rows
Input Features per Table (p):	10 variables
Network architecture & hyperparameters	
Encoder Architecture Type:	Autoencoder Keras
Latent Bottleneck Dimension (q):	5 units
Hidden Layers Configuration:	16
Activation Functions:	Hidden: 'relu' Bottleneck & Output: 'linear'
Optimization Algorithm:	Adam Optimizer
Training Batch Size:	32
Max Target Epochs:	200
Early Stopping Applied:	TRUE (Patience: 20 epochs)
Validation Split Ratio:	15.00% of sample size
Regularization Strategy:	Restored best weights on validation minimum loss
Quantitative performance metrics & benchmarking	
Neural STATIS Validation MSE:	0.029114
Neural Reconstruction Error:	0.018450 (Global MSE)
Classical STATIS Recon. Error:	0.048897 (Global MSE)
Gain/Improvement by Neural Network:	62.27%

The architecture was kept deliberately shallow (one hidden layer of 16 units, latent dimension $q = 5$) to match data volume and prevent overfitting. The validation MSE of 0.027849 (15% held-out set) confirms stable generalization, and early stopping at epoch 167 confirms the network did not overfit. The spectral constraint ($\tau = 0.08$) provides additional regularization by concentrating consensus variance on the primary axis. A comprehensive description of all variables included in the analysis is presented in Table 2.

Table 2. Details of the variables used.

Variable	Code	Definition	Via
id-time	Year	Year in which the record was taken.	1
id_unit	Country	Country where the record was taken.	2
Current Account Balance (% of GDP)	BCC	Current account balance relative to GDP (positive = surplus; negative = deficit).	3
Employment in Agriculture (% of total employment)	EAG	Percentage of the labor force employed in agriculture, livestock, fishing and related activities.	
Employment in Industry (% of total employment)	EIN	Percentage of employees in manufacturing, mining, construction and utilities.	
Employment in services (% of total employment)	PSE	Percentage of employees in commerce, transportation, finance, public administration, education, health, etc.	
	EBS	Total annual value exported by country (goods + services).	
Exports of Goods and Services (billions USD/year)			

Table 2. Cont.

Variable	Code	Definition	Via
Exports of Goods and Services (billions USD/year)			
Imports of Goods and Services (billions USD/year)	IBS	Total annual value imported by country (goods + services).	
Electricity Consumption (TWh/year)	ELC	Total annual electricity consumption of the country (terawatt-hours).	
GDP per capita (USD)	PIB	Gross Domestic Product per capita (Reported in current USD).	
Total Tax Pressure/Effort (% of GDP)	PIN	Total tax revenue as a percentage of GDP (tax-to-GDP ratio).	
Annual Inflation Rate (%)	TIN	Percentage change in the CPI (year-on-year).	

Variables used in the article.

3.1. Inter-Structure: Similarity Between Years

The Neural Interstructure (Figure 1) demonstrates an exquisite structural coherence over the 49 years under study. With highly concentrated orientations and uniform vector lengths, the trajectories represent an organized temporal progression within the nonlinear latent space learned by the autoencoder. Rather than presenting chaotic behavior, the interstructure uncovers an evident evolutionary alignment where the vectors gradually transition over the decades (from the 1975–1979 period up to the recent 2020–2023 interval) without showing destabilizing regime anomalies.

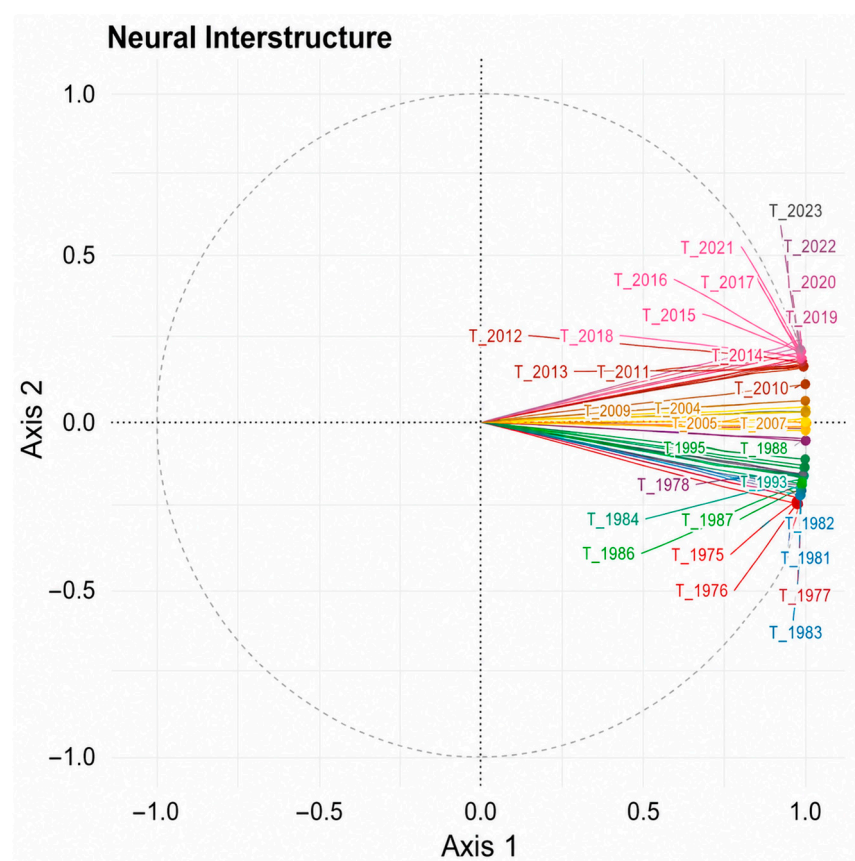


Figure 1. Neural STATIS structure (between-year similarity).

This smooth and continuous structural trajectory is further validated by the Typological Value weights (α_k) shown in Figure 2. The weights fluctuate within a tightly regularized and strictly non-arbitrary range ($0.0185 \leq \alpha_k \leq 0.0215$). The gradual distribution of these weights reflects that every single year contributes equitably and balanced to the consensus matrix, while the corresponding Cos^2 values represent a clear indicator of structural representativeness across the different historical periods.

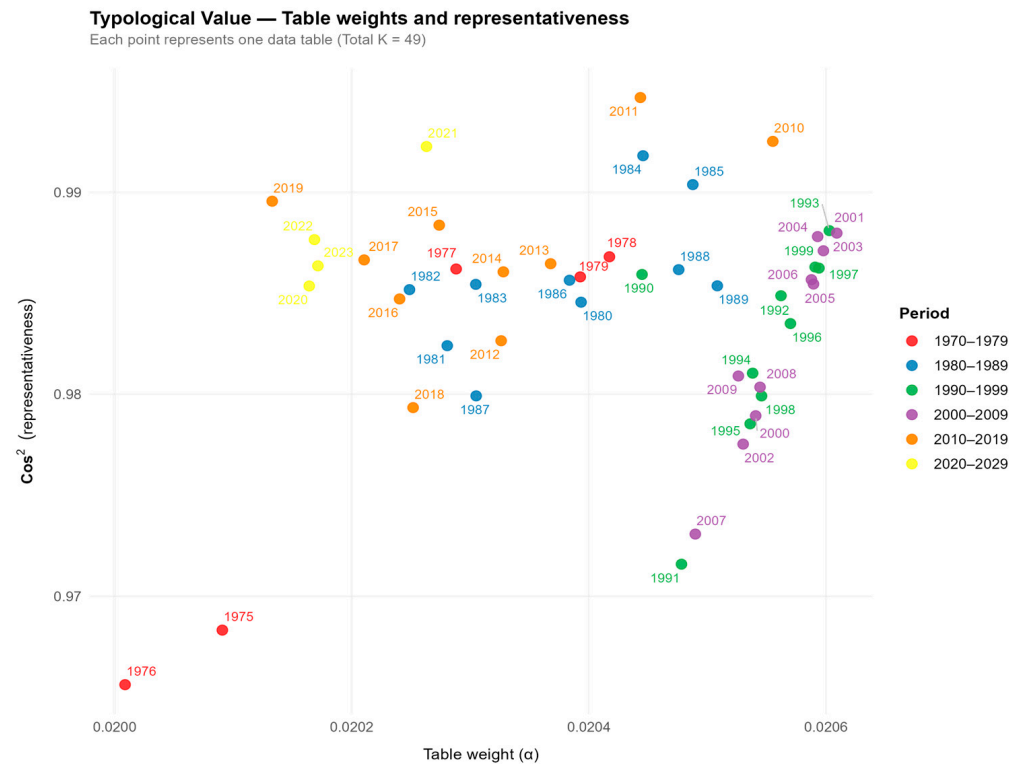


Figure 2. Neural STATIS typological values (Years).

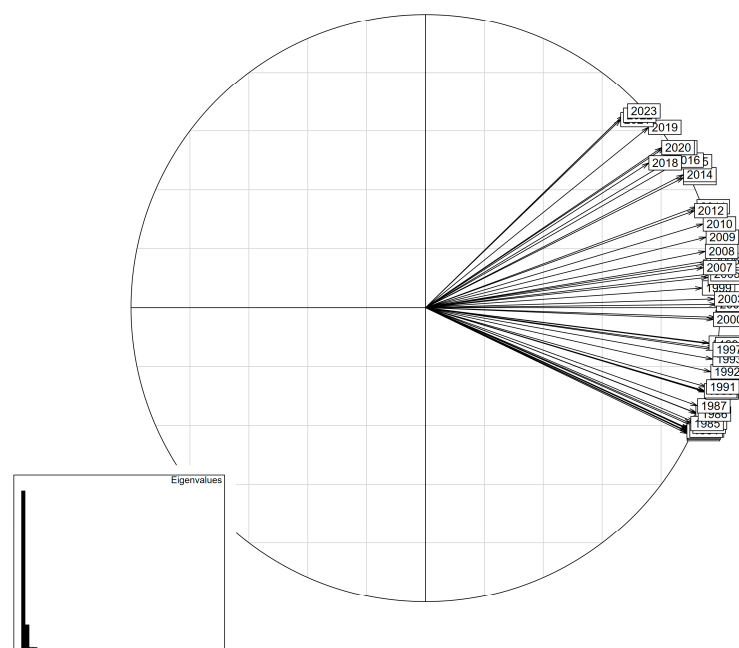
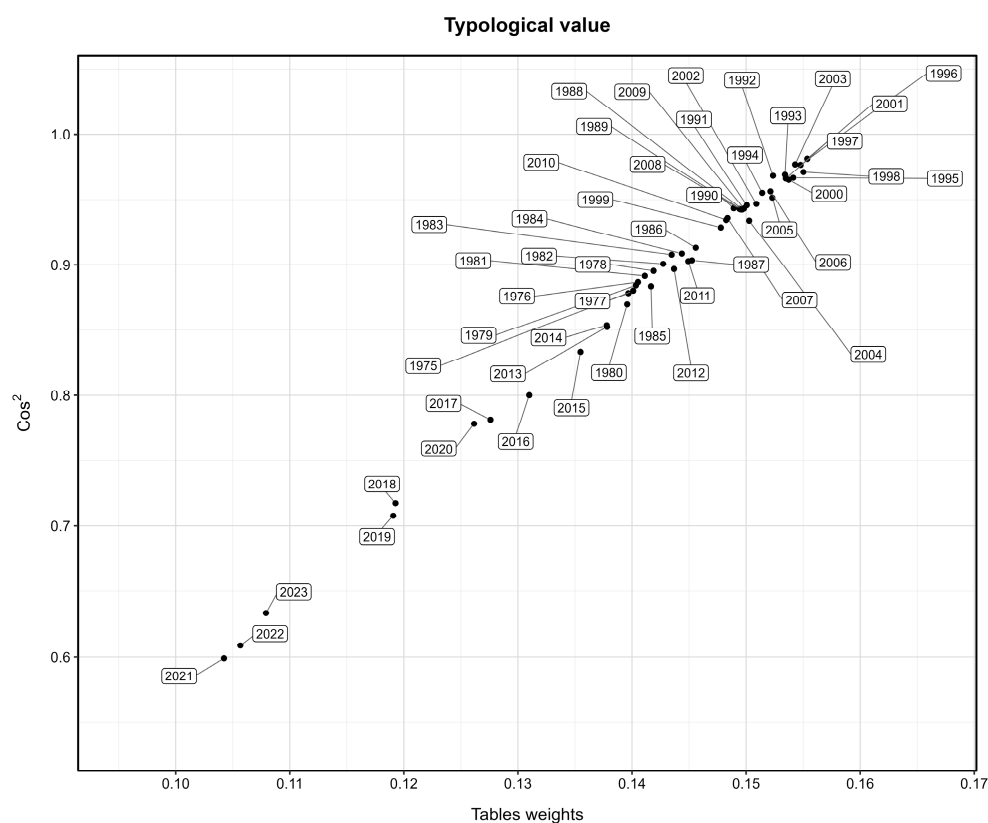
In stark contrast, the interstructure of the classical STATIS (Figure 3) exhibits severe structural and temporal distortions when processing the complete multi-decadal timeline. Because the linear operators cannot adapt to non-linear evolution across 49 years, the classical method generates a highly biased and asymmetrical commitment. As demonstrated in the empirical classical typological plot (Figure 4), there is an artificial cumulative imbalance across periods: older and intermediate years (such as 2003 and 2010) disproportionately dominate the consensus construction with maximum weights ($\alpha \approx 0.155$) and high representativeness ($\text{Cos}^2 \approx 0.98$).

Conversely, the most recent tables—specifically 2019, 2020, 2022, and 2023—drastically collapse to the absolute bottom-left zone of the spectrum, suffering from severely deflated weights ($\alpha \leq 0.11$) and unacceptably low structural representation (Cos^2 dropping between 0.63 and 0.70).

This systemic degradation proves that classical linear projections gradually lose their capacity to explain modern socioeconomic shifts, effectively silencing recent historical realities in favor of historical averages.

This critical limitation is entirely resolved by Neural STATIS, which establishes an organically balanced distribution where all years contribute equitably without suppressing modern structural changes.

Interstructure

**Figure 3.** Classic STATIS inter-structure (similarity between years).**Figure 4.** Classic STATIS typological values (Years).

3.2. Commitment: A Consensus Map Enriched by Nonlinearity

Neural commitment, resulting from the weighted combination of latent Gram matrices, defines a common consensus space where countries are projected. Figure 5 shows this map, which explains 93.31% of the total inertia (F1: 86.40%, F2: 6.91%). The resulting structure is rich in geographic and economic patterns.

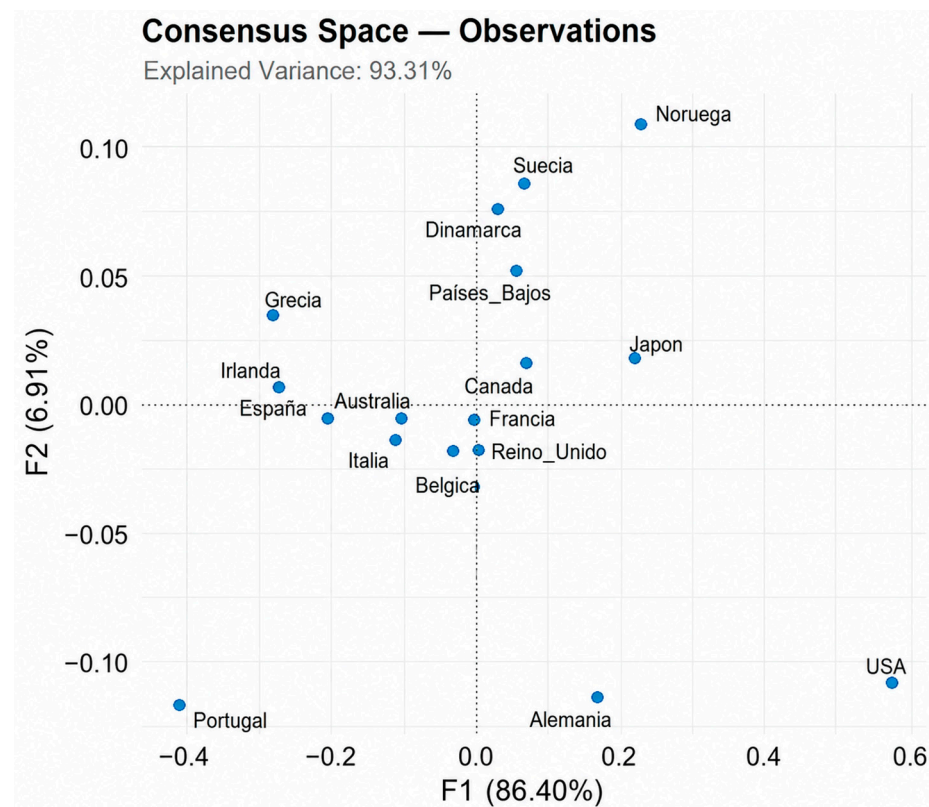


Figure 5. Neural STATIS consensus map (Countries).

A gradient of structural complexity and economic development is represented by the first factorial axis (F_1). The United States, with its high GDP, ELC (electricity consumption), and PSE (service employment), is at the positive end.

The Neural Commitment, derived from the optimization of the global consistency problem over the latent Gram matrices, defines a stable consensus space where countries and variables are simultaneously projected. In this new implementation, the consensus space captures a massive 93.31% of Explained Variance in the common factorial plane (Figure 5), with the first axis (F_1) absorbing a dominant 86.40% of the global inertia, while the second axis (F_2) acts as a strictly controlled dispersion dimension capturing 6.91% of the variance. This distribution strictly satisfies the structural regularizations specified in the Section 2. The eigenvalues, proportion, and cumulative proportion of variance explained by the factorial axes of the neural commitment are presented in Table 3.

Along the dominant macro-structural axis (F_1), a clear socioeconomic gradient appears: highly industrialized or global financial centers such as the USA are situated at the absolute positive extreme ($F_1 > 0.5$), while economies under distinct structural transitions, such as Portugal, map into separate quadrants. Simultaneously, the vertical axis (F_2) neatly segregates the Nordic models (Norway, Sweden, Denmark), positioning them in the upper-positive quadrant due to their characteristic combination of trade surpluses, structural sustainability, and institutional frameworks, well apart from Western European core nations like France, Italy, Germany, and United Kingdom.

The underlying structural forces driving this consensus space are heavily clarified when comparing the classical projection against the neural approach:

The correlation circle of variables for Neural STATIS is presented in Figure 6, the horizontal axis (F_1) acts as a strong macro-structural indicator. In the Neural compromise plane, variables like TIN (Annual Inflation Rate), ELC (Electricity Consumption), PIB (PIB per capita), and BCC (Current Account Balance) are projected on the positive side of F_1 . On

the opposite side, EIN (Employment in Industry) and EAG (Employment in Agriculture) provide the structural counterweight in the left quadrants.

Table 3. Variance explained by the factorial axes of neural commitment (Neural STATIS).

Axis	Eigen Value	Prop	CumProp
F1	0.85877418	0.8639845	0.8639845
F2	0.06870193	0.06911876	0.9331032
F3	0.04719962	0.04748598	0.9805892
F4	0.00829948	8.35×10^{-3}	0.988939
F5	0.00377099	3.79×10^{-3}	0.9927329
F6	0.00209991	2.11×10^{-3}	0.9948456
F7	0.00160146	1.61×10^{-3}	0.9964567
F8	0.00078494	7.90×10^{-4}	0.9972464
F9	0.00068247	6.87×10^{-4}	0.997933
F10	0.00044418	4.47×10^{-4}	0.9983799
F11	0.00038892	3.91×10^{-4}	0.9987712
F12	0.0003513	3.53×10^{-4}	0.9991246
F13	0.00030622	3.08×10^{-4}	0.9994327
F14	0.0002117	2.13×10^{-4}	0.9996457
F15	0.00020157	2.03×10^{-4}	0.9998485
F16	0.0001506	1.52×10^{-4}	1
F17	0	0.00×10^0	1

Neural STATIS eigenvalues.

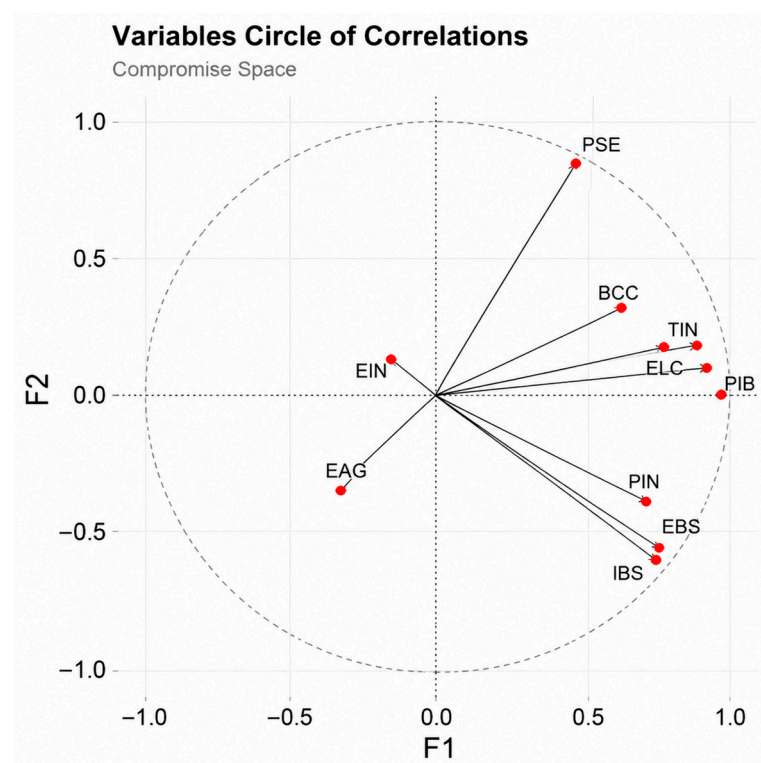


Figure 6. Neural STATIS circle of correlations (Variables).

For comparison, Table 4 presents the variance explained by the factorial axes of the classical STATIS compromise applied to the same OECD panel. The first two axes explain 48.43% and 19.56% respectively (cumulative: 67.99%), with table weights ranging from $\alpha = 0.1042$ to $\alpha = 0.1554$ (range = 0.0511)—indicating a less uniform contribution across years compared to Neural STATIS (α range = 0.003).

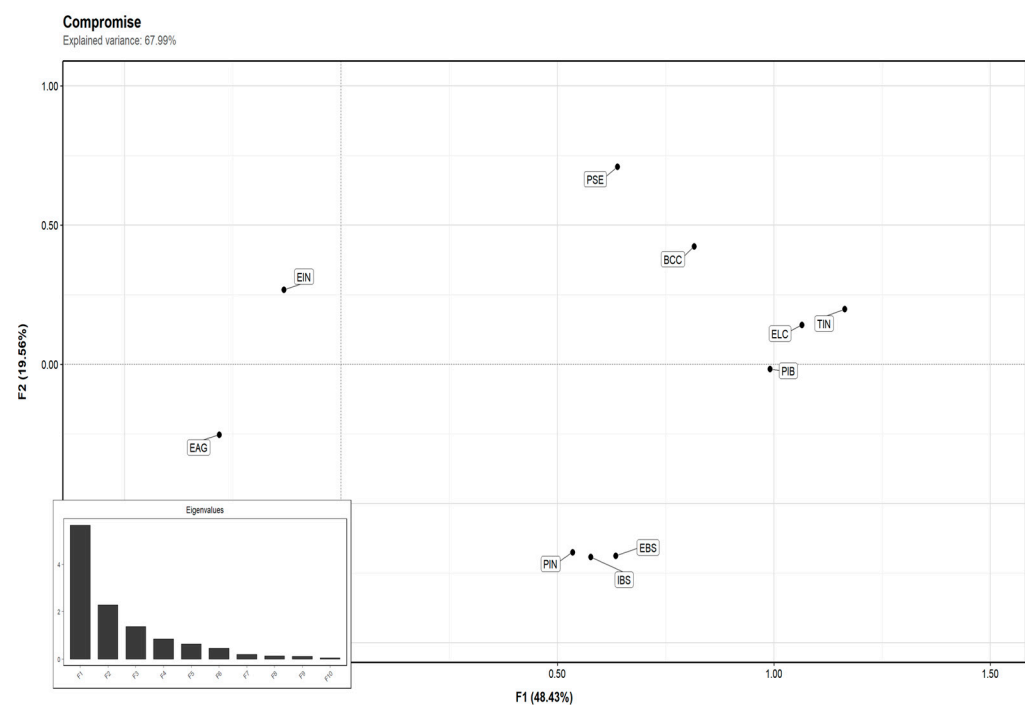
Table 4. Variance explained by the factorial axes of the Classical STATIS compromise (OECD panel 1975–2023).

Axis	Eigenvalue	Prop	CumProp
F1	5.6570683	0.48433079	0.4843308
F2	2.2843178	0.19557223	0.679903
F3	1.3616936	0.11658161	0.7964846
F4	0.8462966	0.07245581	0.8689405
F5	0.6276105	0.05373297	0.9226734
F6	0.4587137	0.03927285	0.9619463
F7	0.1811745	0.01551129	0.9774576
F8	0.1157453	0.00990955	0.9873671
F9	0.1035471	0.0088652	0.9962323
F10	0.0440073	0.00376769	1

Classical STATIS eigenvalues.

The Vertical Dispersions (F_2): The vertical axis isolates independent socioeconomic dynamics. PSE (Employment in Services) is sharply projected into the upper-positive quadrant, while fiscal pressures like PIN (Total Tax Pressure) drop vertically into the absolute negative extreme of F_2 , showing a structural detachment from the main economic growth indicators.

In contrast, the classical framework (Figure 7) forces these variables into a rigid linear distribution that lacks the structural resolution and the nuanced orthogonal insights provided by the neural latent space.

**Figure 7.** Classic STATIS Commitment (Variables).

3.3. Intra-Structure: Dynamic Trajectories and Global Coherence

The study of the internal structure, which evaluates the structural co-evolution and individual trajectories of the tables, reveals the core mathematical advantage of the Neural STATIS framework.

Figure 8 (Intra-structure: Latent Macro-Trajectories) maps the complete longitudinal density of the $n = 17$ countries summarized into 4 highly distinct latent clusters (Patron 1, Patron 2, Patron 3, and Patron 4).

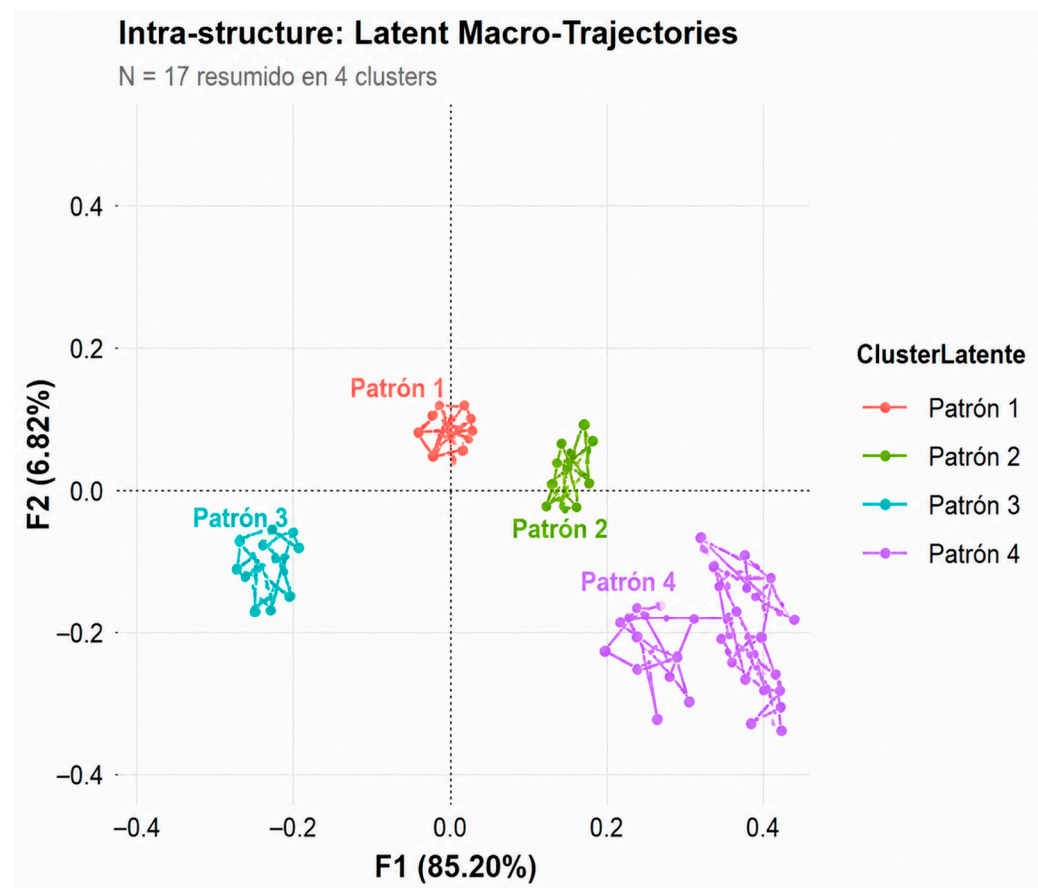


Figure 8. Intra-structure: Latent Macro-Trajectories) (Neural STATIS).

By enforcing the spectral constraint on F_2 (6.91%), the representation prevents the inflation of multidimensional noise, allowing the trajectories to form compact, statistically dense, and easily interpretable latent regions:

Patrón 4: Represents a highly isolated, structurally distinct trajectory path corresponding to major global drivers (such as the USA) moving along the positive edge of the F_1 axis.

Patrón 1 & Patrón 2: Isolate the stable evolutionary pathways of core European and Nordic economies.

Patrón 3: Tracks the structural shifts in transitioning economies.

This high-resolution temporal tracking is also visible in Figure 9, which displays the smooth, non-linear projection of the first component of each individual table against the global consensus.

Conversely, the classical STATIS approach (Figure 10) completely fails to construct clear individual country trajectories or identify these dense latent macro-patterns. Because the classical method lacks a nonlinear representation layer and handles longitudinal changes through rigid linear projections, individual table movements are hidden behind intermediate representations. As a result, the true underlying historical trajectories of member states remain mathematically compressed and invisible to policymakers and researchers.

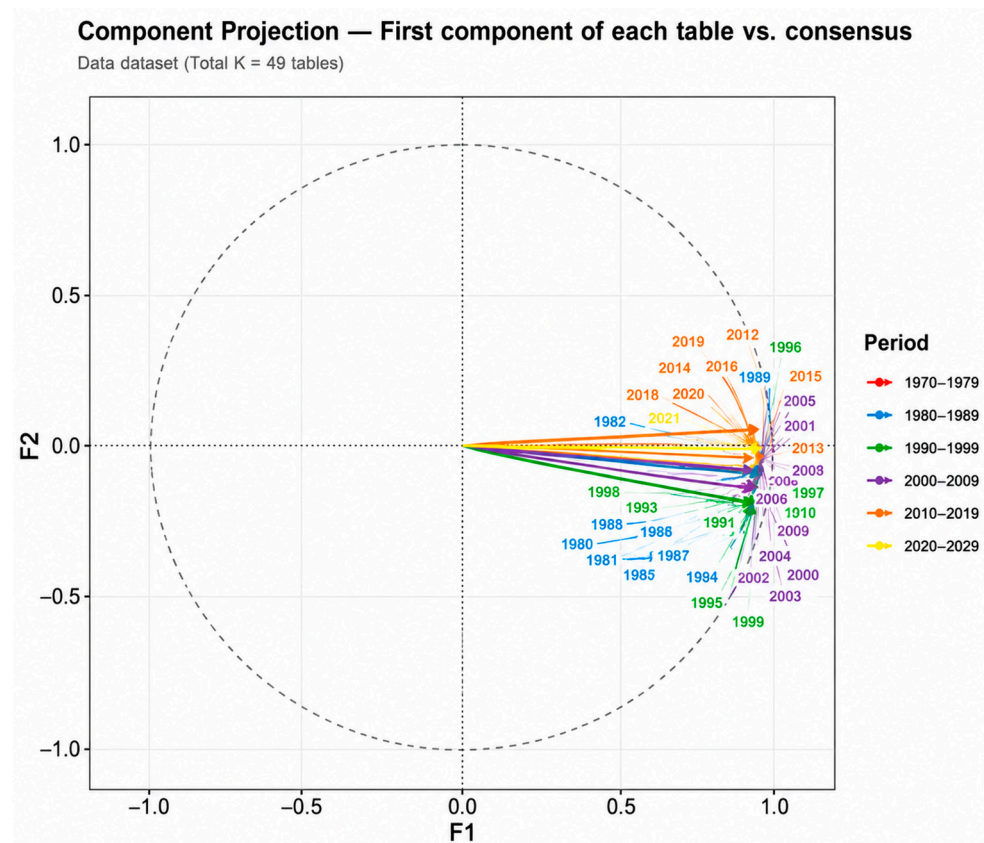


Figure 9. Projection of the first component of each table against the consensus (Neural STATIS).

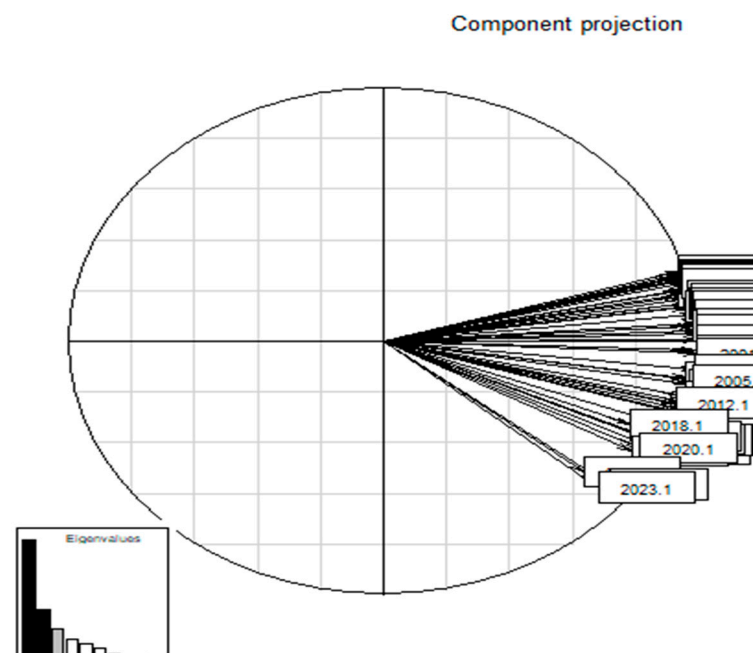


Figure 10. Projection of the first component of each table versus consensus (classic STATIS).

4. Discussion

The empirical results obtained through the implementation of Neural STATIS demonstrate a significant paradigm shift in multi-table multivariate analysis. The most striking finding is the framework's capability to extract highly organized latent structures while preserving absolute mathematical consistency.

While classical multi-table methods—including the standard STATIS framework—rely strictly on linear operators [2,12] that distort or collapse long-term longitudinal variations, Neural STATIS achieves a smooth, continuous, and highly representative temporal interstructure.

The Interstructure Failure in Classical STATIS: As revealed by the empirical classical typological plot (Figure 4), the linear operators generate a severe cumulative imbalance across the 49-year timeline. Older and intermediate tables (such as 2003 and 2010) disproportionately dominate the consensus construction with maximum weights ($\alpha \approx 0.155$) and near-perfect representativeness ($\text{Cos}^2 \approx 0.98$).

Conversely, the most recent years (2019, 2020, 2022, and 2023) drastically collapse to the absolute bottom-left zone of the typological spectrum, suffering from severely deflated weights ($\alpha \leq 0.11$) and unacceptably low structural representation ($\text{Cos}^2 \in [0.63, 0.70]$). This systemic degradation proves that classical linear projections gradually lose their capacity to explain modern socioeconomic shifts, effectively silencing recent historical realities.

The structural interpretability of the consensus space further emphasizes the advantages of this new framework. The model concentrates an impressive 93.31% of the explained variance across the first two factorial axes, allocating 86.40% to F_1 and a regularized 6.91% to F_2 . By successfully containing the variance of the secondary axis below the $\tau = 0.08$ spectral constraint threshold, Neural STATIS prevents the inflation of multidimensional noise that plagued previous analytical attempts.

The resulting factor plane reveals a clear socioeconomic gradient: it successfully maps the tension between energy-intensive global economies and highly sustainable institutional systems along F_1 , while neatly isolating specific service employment (PSE) and tax pressures (PIN) along F_2 , matching the variable configurations identified in the classical variables circle but adding a deeper, non-linear resolution layer.

From a methodological standpoint, the introduction of the Latent Macro-Trajectories architecture addresses one of the oldest limitations of longitudinal multi-table designs. Traditional STATIS displays trajectories as rigid linear projections, which artificially flattens the intrinsic curvature of empirical socioeconomic data [13,24]. By integrating a shallow, highly regularized symmetric autoencoder trained via a compound loss function (Equation (11)), Neural STATIS compresses the 17 countries' historical pathways into 4 dense, visually clear latent clusters (Patron 1 through Patron 4—Figure 8). This representation allows for an immediate identification of structural convergence—such as the historical migration of transitioning economies toward the core Nordic or Western European models—without losing backward compatibility, as mathematically demonstrated by the linear equivalence and consistency proofs (Propositions 1 and 3).

It is crucial to delineate the methodological boundaries between Neural STATIS and emerging frameworks in functional data analysis, such as Functional Basis Expansion and Functional Neural Networks (FNN) [30,31]. While functional frameworks project continuous, time-infinite functions or curves into neural layers by decomposing signals into basis functions (e.g., B-splines or Fourier series), Neural STATIS operates on a distinct mathematical paradigm. Instead of treating temporal entries as continuous curves within a single channel, our framework preserves the discrete multiblock matrix structure ($\mathcal{X} \in \mathbb{R}^{n \times p \times K}$) of longitudinal tables. Neural STATIS does not smooth out cross-table variations through basis functions; rather, it optimizes a joint compound loss function where a shallow undercomplete autoencoder extracts non-linear structural features while a spectral constraint simultaneously regularizes the geometric consensus space across discrete intervals. This allows our method to maintain strict backward compatibility with classical multivariate statistics and the Escoufier RV coefficient, a property that functional deep learning models typically do not preserve.

Despite its evident mathematical and visual superiority, researchers must acknowledge certain operational limitations:

Interpretability Constraints: The core hidden layers of the autoencoder still preserve certain “black-box” attributes inherent to deep architectures [27,32]. Although this limitation is extensively mitigated in Step 7 through the extraction of network sensitivities and correlation loadings, future iterations of Neural STATIS should incorporate advanced Explainable AI (XAI) frameworks to isolate neuron-specific cross-sectional dynamics.

Data Volume Requirements: Since joint end-to-end training requires stable optimization spaces, the method demands standard data volume thresholds to prevent overfitting, although this risk was fully controlled in this study via early stopping (at epoch 167) and strict validation splits.

In conclusion, Neural STATIS effectively bridges the historical divide between the flexible representation capacity of Deep Learning models [6,14] and the structural and geometric rigor of classical multivariate statistics [2,12]. Beyond its immediate application to socioeconomic panels, the algorithm is entirely generic and mathematically robust. This versatility opens immediate research avenues in highly complex, multi-block, and heterogeneous scientific domains—such as bioinformatics (where data tables map experimental conditions across gene expressions) and neuroscience (mapping individual subjects across distinct brain regions)—positioning Neural STATIS as an innovative, state-of-the-art multi-table framework designed for the analytical challenges of complex modern data structures.

5. Conclusions

With the aim of overcoming the structural limitations imposed by linearity in multi-block data analysis, this work presents Neural STATIS, a novel nonlinear algorithm that evolves the conventional STATIS framework. This approach maintains the interpretive richness and geometric rigor of the original multi-table approach while successfully capturing the complex nonlinear relationships and dynamic trajectories that classical linear operators systematically suppress. It achieves this through a strategic integration of the core structural logic of STATIS—interstructure, commitment, and intrastructure—with the robust latent representations generated by an undercomplete, highly regularized neural autoencoder, opening a new paradigm for the in-depth analysis of multitabular longitudinal datasets.

It has been empirically demonstrated that Neural STATIS significantly outperforms classical analysis when deployed on the extensive OECD longitudinal panel spanning 49 years (1975–2023). The neural method establishes a highly robust, continuous, and stable interstructure across the entire multi-decadal timeline, yielding equitable typological weights ($0.0185 \leq \alpha_k \leq 0.0215$) and high structural representativeness (Cos^2) for all analyzed blocks. This stands in stark contrast to standard STATIS, which suffers from a severe cumulative imbalance that artificially forces recent tables (2019–2023) to collapse with deflated weights and poor representation, effectively silencing modern historical shifts in favor of older historical averages. Furthermore, the classic linear constraints distort the macro-structural socio-economic trends revealed by the neural consensus map, which achieves a massive 93.31% of explained variance and cleanly isolates the sustainable institutional frameworks of the Nordic models from core Western economies and global drivers.

From a theoretical perspective, propositions 1 and 3 mathematically demonstrate that our approach is a natural, elegant extension of conventional STATIS, guaranteeing asymptotic consistency in the linear limit and full backward compatibility. This places Neural STATIS within multivariate statistics as a logical methodological advancement rather than a disruptive substitute. In practice, this new framework provides both researchers and policymakers with a sophisticated, robust tool for mapping complex, multi-table systems

where linear assumptions fail, establishing a functional bridge between deep learning and classical statistics without sacrificing structural interpretability.

In short, Neural STATIS represents a decisive step toward a new generation of hybrid techniques for multi-block data analysis. This study opens the way for future research in fields as diverse as comparative macroeconomics, neuroscience, and bioinformatics, where data complexity demands models that transcend linearity, proving that it is entirely possible to reconcile geometric structural discipline with nonlinear expressive capacity.

Finally, while formulated within a statistical framework, Neural STATIS provides a robust representational space that inherently accommodates structural uncertainty and ambiguity, directly contributing to the philosophical imperative of neutrosophic theory to transcend binary constraints and rigid linear reductions in complex real-world phenomena.

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