Innovation ecosystems: segmentation and analysis of OECD countries

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Abstract

This study examines innovation patterns among Organization for Economic Cooperation and Development (OECD) member countries using data from the 2023 Global Innovation Index. It contributes to the field by applying exploratory factor analysis combined with hierarchical cluster analysis using Ward's method, which provides an informed taxonomy of innovative ecosystems in developed economies. Unlike previous studies, this paper uses dimensional reduction and clusters to categorize innovative capabilities using a three-dimensional typology and three distinctive country clusters. The results revealed differentiated patterns of innovative capabilities among countries, emphasizing the importance of the institutional environment, infrastructure and sustainability in innovative performance.

Keywords: innovative ecosystems; cluster analysis; innovative capabilities; OECD countries; innovation typology.

1. INTRODUCTION

In an increasingly globalized world, innovation is considered a fundamental pillar for economic and social development (Nakano *et al.*, 2022; Cui and Li, 2022). In this context, countries are constantly searching for effective strategies to strengthen and enhance their innovation ecosystems (Huang *et al.*, 2023). The Organization for Economic Cooperation and Development (OECD), comprised of some of the world's most advanced and dynamic economies, is a valuable resource for analyzing and understanding how innovation and creativity contribute to the economic growth and social well-being of nations.

Leading nations in innovation enjoy an economic advantage and set standards and practices that reverberate throughout international value chains and business ecosystems (Liao *et al.*, 2023; Rossi *et al.*, 2023). This dynamic underscores the strategic importance of innovation as a crucial element transcending geographical boundaries and economic sectors (Serrano, 2016). A nation's ability to innovate determines its capacity to adapt to rapid and often disruptive changes in the global economy, which is essential for sustaining long-term economic growth and social progress (Giraldo *et al.*, 2024; Huang, 2024).

From a methodological perspective, OECD countries were selected as the subject of analysis based on specific criteria and theoretical foundations because they are comparable in terms of data collection systems and innovation indicators, which are essential elements for robust multivariate analysis. Theoretically, the OECD is a group of similar, developed economies that have reached critical thresholds of institutional capacity and technological infrastructure. This makes it possible to identify differentiated innovation patterns without the distortions introduced by economies with extreme structural disparities. Additionally, OECD countries account for approximately 70% of global GDP and attract the largest share of global investment in R&D, making them an important analytical space for understanding the dynamics of innovation that will later spread to other economies.

Despite existing literature on innovation, there is a gap in our understanding of how its various components specifically interact within OECD countries. This gap led to the following research question: What patterns of innovation are observed among OECD member countries? How can these countries be grouped in relation to their innovation capabilities?

This research is based on the assumption that OECD countries have different configurations of innovation capabilities that can be grouped into distinctive patterns based on three implicit dimensions: institutional strength and creativity; infrastructure and capital for innovation; and sustainability and knowledge diffusion.

The study also suggests a natural segmentation of OECD countries into three groups according to their innovation profiles: integral leaders, who have balanced strengths across all dimensions; institutional specialists, who have comparative advantages in the regulatory environment and creativity; and countries with emerging capabilities concentrated in sustainability and the diffusion of knowledge.

To address this issue, the study focused on analyzing the innovation sub-indices in OECD countries using the Global Innovation Index 2023 as a reference, which assesses the performance of innovation ecosystems worldwide (Coutinho and Au-Yong-Oliveira, 2023). Through the application of dimension reduction techniques and cluster analysis, the study sought to identify strategic groupings of countries and to examine significant differences between them in terms of their innovative capacity.

The methodological and practical contributions of this study to existing literature are significant, as exploratory factor analysis and cluster analysis provide a deeper understanding of the complex interactions between the variables driving innovation. Furthermore, by revealing how OECD countries cluster around these dimensions, the study provides practical insights for differentiated policy development and offers a framework for international collaboration and strategic benchmarking. This research serves as an analytical tool for policymakers, researchers and entrepreneurs by offering detailed insight into the innovation ecosystems of OECD member countries.

The paper consists of six sections, including this introduction. The second section describes the theoretical and contextual framework and develops the conceptual foundations of innovation ecosystems. The third section describes the research design, indicator selection and analytical strategy. The fourth section presents the factorial and cluster analysis findings. The fifth section discusses, interprets and validates the proposed conceptual framework. The sixth section summarizes the theoretical contributions and implications for innovation policy.

2. THEORETICAL AND CONTEXTUAL FRAMEWORK

The roots of the modern understanding of innovation can be found in classical theories, including Schumpeter's seminal contribution (1942). His concept of "creative destruction" revolutionized the way we understand economic development. He argued that innovation drives the creation of new products and processes and leads to the transformation or disappearance of existing ones. This process is the engine of change and economic progress in the capitalist system, where cycles of economic renewal and transformations in market structure are closely intertwined with the emergence of innovation (Markard, 2020).

Building on Schumpeter's (1942) perspective on innovation mechanisms, Rogers (2003) offered a social view of the innovation process. His theory of the diffusion of innovations examines how new ideas or technologies are adopted and spread within society. It emphasizes the process through which members of a community or social group acquire innovations and highlights the crucial factors that influence this process. This social perspective of innovation lays the foundation for understanding how innovations transcend the individual sphere to become systemic phenomena and leads to the analysis of national innovation systems.

National Innovation Systems (NIS) are a fundamental theoretical element for understanding the vitality and direction of business and national innovation. Initially developed by Freeman (1987) and later detailed by Lundvall (1992) and Nelson (1993), NISs are defined as interconnected networks of public and private institutions that initiate, import, modify and disseminate new technologies (Freeman, 1987). NISs operate under the principle that innovation results from complex interactive processes between multiple actors, including companies, universities, research institutes, government agencies and financial organizations. The effectiveness of these systems depends on the quality of interconnections, knowledge flows and coordination mechanisms between these components, not just on the components themselves (Lundvall, 2007).

In the specific context of developed countries, such as those in the OECD, NISs differ from those in emerging economies in that they have consolidated higher education and research institutions, stable regulatory frameworks that protect intellectual property, developed capital markets to finance innovation and advanced technological infrastructure that facilitates the transfer of knowledge (Edquist, 2005). These characteristics form the basis for what contemporary literature refers to as innovative ecosystems.

Evolving from national system concepts, innovative ecosystems represent a conceptual evolution that incorporate elements of complex systems theory and network perspectives. Innovative ecosystems are open systems formed and expanded by a business-focused innovation consortium that includes universities, investors, industry, government and other combinations of interested parties. These ecosystems are formed through clustering reactions of innovation elements, innovation value chains and value networks. This includes dynamically evolving innovation subclusters in research, development and application (Huang *et al.*, 2023).

This operational definition distinguishes innovative ecosystems from related concepts by highlighting three fundamental characteristics:

Business centrality: Unlike NISs, which adopt a national perspective, innovative ecosystems are organized around specific business clusters that act as catalysts for innovative activity.

Clustering dynamics: Ecosystems exhibit emergent properties derived from "clustering reactions" that generate localized synergies and network effects.

Adaptive evolution: Innovative ecosystems are characterized by dynamically evolving subclusters that continuously adapt to technological and market changes.

For this study, we adopted an operational definition that conceptualizes innovation ecosystems as multidimensional configurations of institutional capabilities, technological infrastructure and knowledge diffusion mechanisms that determine a national economy’s the aggregate innovative performance. This definition is complemented by theoretical developments on open innovation and intersectoral collaboration.

Alongside these conceptual developments, Drucker (1993) emphasizes that innovative ecosystems flourish in environments where knowledge is shared and utilized to generate value, underscoring collaboration as a pivotal aspect of this process. Similarly, networks and intersectoral collaboration involving businesses, academia and governments have become critical in fostering an environment conducive to innovation (Bodin, 2017).

Chesbrough (2003) introduces the concept of open innovation, arguing that integrating external ideas and technologies with internal resources is essential to the innovation process. This paradigm fosters a more inclusive and diverse innovation ecosystem where cooperation between different entities is balanced with healthy competition.

Effective collaboration between various agents, including academia, the public sector, the productive sector and civil society, requires knowledge management (Toro *et al.*, 2022). Effective knowledge management facilitates the coherent articulation of the actions of these agents and highlights the need for further studies to optimize team effectiveness and enhance knowledge integration in institutions.

These theoretical foundations naturally lead to the need to operationalize innovative ecosystems through specific indicators that capture their multiple constituent dimensions. Based on literature regarding NIS and innovation ecosystems, this study identifies three fundamental theoretical dimensions that structure its empirical analysis.

The first dimension, Institutional Environment and Creativity, captures the quality of the institutional framework supporting innovative activity. This dimension includes the effectiveness of formal institutions, such as regulatory frameworks and intellectual property protection, as well as informal institutions, such as business culture and social norms that favor innovation. The selected indicators cover the institutional, regulatory and business environments, as well as manifestations of digital creativity. This reflects North's (1990) conceptualization of the role of institutions in economic activity.

The second dimension, Infrastructure and Capital for Innovation, operationalizes the material and financial capacity available to sustain innovative processes. This dimension incorporates elements of physical infrastructure (Information and Communication Technologies [ICTs], general infrastructure), specialized human capital (knowledge workers), financial resources (credit, investment) and market sophistication. This conceptualization is based on endogenous growth theory (Romer, 1990), which emphasizes the role of physical and human capital in generating innovation.

The third dimension, Sustainability and Diffusion of Knowledge, captures mechanisms and results of transferring and applying innovative knowledge. It includes indicators of knowledge creation, impact and diffusion, as well as ecological sustainability considerations and creativity in goods and services. This dimension is based on knowledge spillover theories (Jaffe *et al.*, 1993) and considers the growing importance of sustainable innovation in developed economies.

To validate this conceptual framework empirically, it must be contextualized within existing research. A literature review by Rodríguez and Quintero (2021) shows that most studies on innovation capabilities focus on developed countries. However, when analyzing business innovation capabilities in the Latin American context, they found heterogeneous variables that varied according to the countries and specific contexts studied.

Recent studies have employed various methodological approaches to analyze innovation patterns. For instance, Polyakov (2024) used multivariate analysis methods to identify innovation clusters in leading countries in the Global Innovation Index, revealing significant differences in innovation ecosystems within the global competitive context. However, this study focused on leading countries without considering heterogeneity within the OECD group. Additionally, Coutinho and Au-Yong-Oliveira (2023) used descriptive analyses of the Global Innovation Index and the European Innovation Scoreboard for Portugal, Sohn et al. (2015) used structural equation models to analyze the relationships between components of the Global Innovation Index.

This study differs from previous research in that it applies exploratory factor analysis techniques combined with hierarchical cluster analysis in OECD countries specifically. This study also provides an empirically grounded typology of innovative ecosystems based on underlying dimensions and integrates sustainability considerations into the analysis of innovative capacities. This is an element that has largely been overlooked in previous comparative studies. The choice of

OECD countries as the subject of this study is based on previous research recommendations, such as those by Bate *et al.* (2023), who highlight the need for more detailed, stratified analyses of innovation performance. This recommendation is particularly relevant because the authors identified that broad global or regional analyses tend to hide significant disparities in innovative capacities between countries with similar levels of development. Focusing on OECD countries allows for a more rigorous and homogeneous comparison since these countries share comparable institutional, economic and regulatory characteristics. This enables isolation of specific factors that drive or limit innovation.

The interaction between classical theories and contemporary trends in innovation underscores the importance of understanding it within a globalized, technologically advanced context. This provides the conceptual basis for the empirical analysis that constitutes the central objective of this study, which is discussed below.

3. METHOD

This research adopts a quantitative, descriptive, explanatory design based on multivariate analysis. Using an exploratory research approach, the study identifies underlying structures in the data through dimensional reduction techniques and cluster analysis. This allows for the construction of an empirically grounded typology of innovative ecosystems.

The analysis uses data from the 2023 Global Innovation Index (GII) rather than the 2024 version for specific methodological reasons that ensure the robustness of the results. First, the 2023 GII offers greater temporal stability because it incorporates data with a sufficient stabilization period for OECD countries. This avoids the volatility derived from the recent methodological adjustments present in the 2024 version. Additionally, the 2023 GII ensures greater consistency in the time series because the selected indicators maintain methodological continuity with previous years. This continuity is essential for ensuring comparability between countries. Finally, when the study was designed in the first quarter of 2024, the 2023 GII had all the necessary data for the 36 OECD countries included in the study.

Selecting variables for analysis required the establishing rigorous criteria to ensure the conceptual and empirical validity of the study. The criteria for selecting indicators for the 2023 GII were based on their ability to operationalize the theoretical dimensions identified in the conceptual framework. Nineteen indicators were selected, which cover crucial aspects of innovation ecosystems, including institutions, human capital, infrastructure, market and business sophistication, knowledge and technology products, and creative outlets. Theoretically and empirically, this selection is justified: the selected indicators show significant correlations with innovative performance measures in previous studies (Al-Sudairi and Bakry, 2014; Sohn *et al.*, 2015); and cover the three conceptual dimensions identified in the theoretical framework. They also guarantee availability and comparability for all OECD countries included in the analysis.

After establishing the selection criteria, the analytical strategy was structured into two complementary phases to meet the study's objectives. The first phase uses exploratory factor analysis to identify the latent dimensions underlying the data. The second phase uses cluster analysis to develop a typology of countries based on the identified dimensions.

To identify the latent dimensions, exploratory factor analysis was implemented using the principal component method with Varimax orthogonal rotation (Field, 2013). This technique was chosen because of its ability to identify latent dimensions underlying complex sets of variables.

Sample adequacy criteria include Bartlett's sphericity test, which assesses the presence of significant correlations between variables. For factor analysis to be considered appropriate, the *p*-value must be less than 0.001. The Kaiser-Meyer-Olkin (KMO) measure quantifies the adequacy of the correlation matrix and a value greater than 0.7 is considered acceptable according to the criteria established by Field (2013).

Determining the optimal number of components to retain is based on convergence of several methodological criteria that ensure the robustness of the factor solution. Three components were retained based on Kaiser's criterion (1960), which recommends retaining components with eigenvalues greater than 1.0. Additionally, the first three components must explain at least 60% of the total variance, which exceeds the threshold considered adequate for exploratory studies in the social sciences, as established by Hair et al. (2008). Theoretical consistency of the extracted components is also important; they must correspond to the conceptual dimensions set out in the study. Finally, the sedimentation graph must show a clear turning point after the third component, which reinforces the soundness of the decision.

After identifying the latent dimensions through factor analysis, we implemented a hierarchical cluster analysis using Ward's method with Euclidean squared distance. This methodological combination is appropriate for the type of data being analyzed. Ward's method was chosen because it minimizes the sum of squares within each group. This optimizes internal homogeneity and heterogeneity between groups, favoring efficient partitioning of the dataset (Ward, 1963; Murtagh and Legendre, 2014).

Squared Euclidean distance is appropriate for standardized continuous variables because it provides a direct measure of geometric dissimilarity between observations. Furthermore, the hierarchical approach allows visualization of the clustering process using a dendrogram, facilitating identification of the optimal number of clusters and structured interpretation of the results.

The decision to establish three clusters is based on a combination of statistical and theoretical criteria. The elbow criterion, applied to the analysis of the objective function, identifies an inflection point in the sum of squares within groups. This indicates a solution that minimizes information loss without overfitting the model. Conceptually, the three-group solution should offer differentiation consistent with the literature on types of innovation systems, supporting its substantive interpretability. Additionally, analyzing agglomeration coefficients should reveal significant shifts indicating mergers between clearly differentiated clusters, which would reinforce the robustness of this partition.

After the hierarchical analysis, we applied *K*-means analysis as a method for validating and refining the solution. This dual procedure enables us to use the hierarchical method to determine the number of groups, apply *K*-means to optimize the final country assignment to clusters and evaluate the solution's stability by comparing the methods. The cluster solution is considered valid if the agreement between the two methods exceeds 90%.

Statistical validation of differences between clusters is performed using a multivariate analysis of variance (ANOVA), confirming that the groupings represent significant differences rather than methodological artifacts. This technique validates the developed typology, ensuring that the identified groups present statistically significant differences in the analyzed dimensions.

Prior to all analyses, data preparation procedures were implemented to ensure the validity of the results. All variables were standardized using Z-scores (mean=0, standard deviation=1) to ensure comparability between indicators with different measurement scales and to avoid biases derived from dissimilar magnitudes. The analysis was performed using SPSS v24, a statistical software program selected for its robustness in multivariate analysis, capable of handling complex data sets and offering specialized procedures for factorial and cluster analysis (Hair *et al.*, 2008; Field, 2013).

It is important to recognize the methodological limitations inherent in the design adopted in order to properly contextualize obtained results. This design has specific limitations, such as a cross-sectional analysis that does not capture the temporal dynamics of innovation, dependence on indicators the available GII 2023 indicators without incorporating additional contextual variables, and a focus on OECD countries that limits generalization to other economic contexts. These limitations do not compromise the internal validity of the study but should be considered when generalizing the findings.

4. RESULTS

According to Hair *et al.* (2008), factor analysis is a robust multivariate technique that reveals the underlying structure of complex data sets by grouping them into cohesive sets that exhibit significant mutual correlation. In other words, it reveals the underlying patterns of association between the studied variables. Implementing this method facilitates identifying the dimensions of innovation in the countries studied and the specific variables aligning with each dimension.

To accomplish this, it is necessary to determine Bartlett's matrix correlation (1950), which provides the probability or statistical test to analyze the presence of significant correlations between variables. The results were significant at $p < 0.001$, which is adequate for factor analysis and requires at least $p < 0.05$. The KMO test measures the suitability of the data for quantifying the degree of correlation between the variables. It reached a value of 0.757, which, according to Field (2013) is adequate for factor analysis (see Table 1).

Table 1. KMO and Bartlett's Test

Kaiser-Meyer-Olkin measure of sampling adequacy	.757
Bartlett's sphericity test	
Approx. Chi-squared	587.147
gl	171
Sig.	.000

Source: prepared by the authors.

Next, we ran the principal component factor analysis model, which, according to Hair *et al.* (1998), considers total variance and estimates factors containing low proportions of unique variance. Based on this, we performed an orthogonal rotation using the Varimax method (Field, 2013). Table 2 shows the reduction to three components, which cover a total of 69.651% of the total variance of the phenomenon. This is considered good for an exploratory study.

Table 2. Total variance explained

Component	*Initial eigenvalues*			*Sums of squared extraction loads*			*Sums of squared rotation loads*		
	Total	*% of variance*	*% accumulated*	*Total*	*% of variance*	*% accumulated*	*Total*	*% of variance*	*% accumulated*
1	8.966	47.188	47.188	8.966	47.188	47.188	6.903	36.331	36.331
2	2.545	13.396	60.584	2.545	13.396	60.584	3.563	18.750	55.081
3	1.723	9.068	69.651	1.723	9.068	69.651	2.768	14.570	**69.651**

Note: extraction method: principal component analysis.

Source: prepared by the authors.

Table 3 shows the results of the principal component analysis, which demonstrate the proportion of the variance of each variable that is captured by the identified components. Thus, the communalities are very close to unity, meaning that the results are highly reliable.

Table 3. Communalities

	Initial	*Extraction*
Institutional environment	1.000	.921
Regulatory environment	1.000	.750
Business environment	1.000	.770
Innovation and development	1.000	.871
ICTs	1.000	.540
General infrastructure	1.000	.632
Ecological sustainability	1.000	.701
Credit	1.000	.694
Investment	1.000	.461
Market diversification	1.000	.748
Knowledge workers	1.000	.514
Innovation links	1.000	.811
Knowledge absorption	1.000	.477
Knowledge creation	1.000	.846
Impact of knowledge	1.000	.668
Diffusion of knowledge	1.000	.811
Intangible assets	1.000	.599
Creativity in goods and services	1.000	.661
Online creativity	1.000	.759

Note: extraction method: principal component analysis.

Source: prepared by the authors.

Meanwhile, Table 4 shows the main component analysis, revealing the three factors grouped within the analysis.

Table 4. Rotated component matrix

	Component		
	1	2	3
Institutional environment	**.920**	-.174	.211
Business environment	**.857**	.071	.176
Online creativity	**.839**	-.004	.234
Regulatory environment	**.823**	-.089	.255
General infrastructure	**.731**	.312	-.022
Innovation links	**.720**	.395	.370
Creation of knowledge	**.713**	.527	.246
ICTs	**.683**	.271	-.010
Credit	**.631**	.544	.002
Investment	**.588**	.245	.235
Knowledge absorption	**.550**	.335	.251
Knowledge workers	**.508**	.219	.456
Market diversification	-.195	**.839**	-.080
Intangible assets	.224	**.732**	-.113
Innovation and development	.587	**.705**	.171
Impact of knowledge	.194	**.654**	.451
Diffusion of knowledge	.178	.385	**.794**
Ecological sustainability	.033	-.295	**.782**
Creativity goods and services	.327	-.023	**.744**

Notes: extraction method: principal component analysis. Rotation method: Varimax with Kaiser normalization.
Source: prepared by the authors.

The principal component analysis revealed an underlying three-dimensional structure in the data and identified three main components that explain most of the variance in the innovation indicators. These components provide a multifaceted view of innovation ecosystems in the countries included in the sample:

Component 1: Institutional environment and creativity

This component has high factor loads on variables associated with the institutional and regulatory framework, including the institutional and business environments, online creativity and the regulatory environment. The grouping of these variables suggests a significant interrelationship between the strength of institutions and a society's ability to encourage innovation and creativity.

It also incorporates infrastructure and innovation links, indicating a synergy between structural and dynamic factors in creating an innovative ecosystem. This combination underscores the importance of a robust institutional framework as a catalyst for innovative activity, facilitating interaction between various agents in the innovative ecosystem.

Component 2: Infrastructure and capital for innovation

This component focuses on the tangible and intangible aspects that underpin innovative capacity. These include variables related to physical and financial infrastructure, such as market diversification, intangible assets, investment in innovation and development and the impact of knowledge.

The grouping of these variables highlights the critical importance of investment and strategic resource allocation in fostering innovation. This component reflects the ability of a region or country to effectively mobilize and deploy its resources, both financial and knowledge-based, and translate them into tangible innovative results. It suggests that robust infrastructure and the availability of capital are essential to sustaining and accelerating innovation processes.

Component 3: Sustainability and diffusion of knowledge

The third component integrates variables associated with ecological sustainability and the diffusion of knowledge, including creativity in goods and services. It also represents a crucial dimension that goes beyond merely generating innovations. It encompasses a country's capacity to disseminate knowledge effectively and sustainably.

The inclusion of ecological sustainability in this component indicates the increasing integration of environmental considerations into innovation and knowledge diffusion processes.

Grouping these variables indicates that most advanced countries in this domain can generate innovative knowledge and solutions and possess effective mechanisms for disseminating this knowledge and translating it into creative, sustainable goods and services. This underscores the importance of a holistic approach to innovation, which considers not only the creation of new knowledge, but also its practical application and long-term impact on society and the environment.

Cluster analysis

Once the innovation determinants in the sample countries were identified, cluster analysis with the Ward method was used to classify them. The Ward method is widely recognized and used in cluster analysis due to its effectiveness in minimizing the sum of squares within each group throughout each partition of the data set (Ward, 1963). The main objective of this method is to form clusters such that the total variance within each cluster is minimized (Ramadhan *et al.*, 2020; Murtagh and Legendre, 2014).

Cluster analysis is a fundamental tool for identifying patterns and structures in complex data sets. This technique facilitates interpretation and decision-making processes by effectively grouping information and emphasizing the resulting heterogeneity between groups (Hair *et al.*, 1999).

Comparison of results

The Ward method analysis shows the existence of three clusters (see Table 5). Similarly, the dendrogram (Figure 1) illustrates how countries are grouped according to hierarchical cluster analysis using the Ward method, which aims to form internally coherent groups.

Table 5. Case summaries

			Countries
Ward Method	1	1	Germany
		2	Austria
		3	Belgium
		4	South Korea
		5	Denmark
		6	EU
		7	Finland
		8	France
		9	Iceland
		10	Japan
		11	Netherlands
		12	United Kingdom
		13	Sweden
		14	Switzerland
		Total N	14
			Countries
Ward Method	2	1	Australia
		2	Canada
		3	Iceland
		4	Luxembourg
		5	Norway
		6	New Zealand
		Total N	6
			Countries
Ward Method	3	1	Chile
		2	Slovenia
		3	Slovakia
		4	Spain
		5	Estonia
		6	Greece
		7	Hungary
		8	Ireland

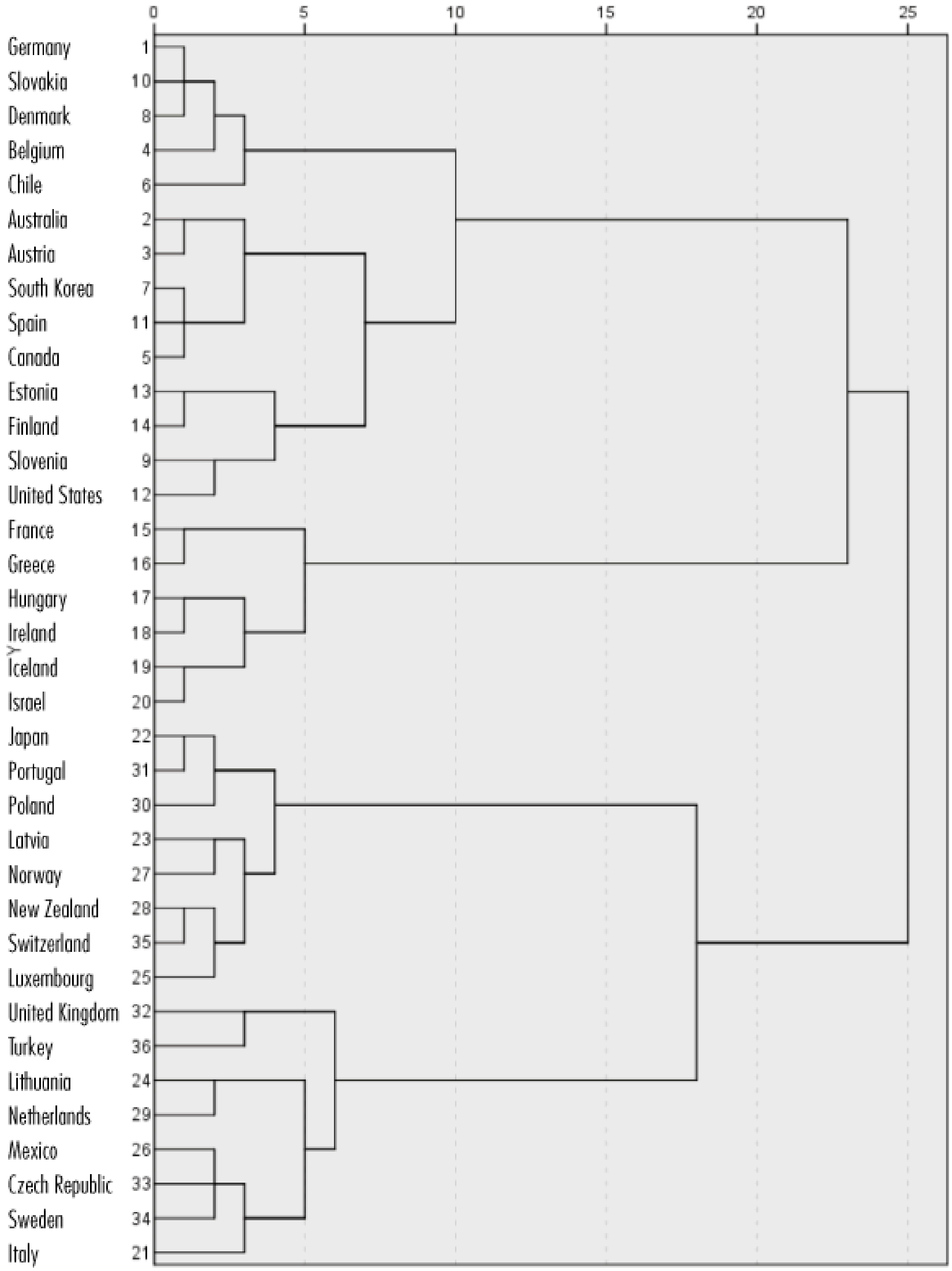
	9	Italy
	10	Latvia
	11	Lithuania
	12	Mexico
	13	Poland
	14	Portugal
	15	Czech Republic
	16	Turkey
	Total N	16
Total N		36

Source: prepared by the authors.

In the dendrogram, horizontal lines represent links between clusters or countries. The height at which the lines on the horizontal axis represents the distance or dissimilarity between the clusters or countries.

Figure 1. Dendrogram using Ward's linkage

Combination of rescaled distance clusters



Source: prepared by the authors.

Three main groupings can be observed:

- Cluster 1 (innovation leaders): comprises 14 countries that are grouped together, i.e., they share similar characteristics in the analyzed innovation indicators. This cluster includes highly developed economies and innovation leaders such as: Germany, Austria, Belgium, South Korea, Denmark, the United States, Finland, France, Iceland, Japan, the Netherlands, the United Kingdom, Sweden and Switzerland.

- Cluster 2 (competitive innovation): made up of six countries, including nations with robust economies and good innovation performance, albeit with slightly greater differences than the first group. This cluster includes countries such as Australia, Canada, Iceland, Luxembourg, Norway and New Zealand.
- Cluster 3 (emerging innovation): This is the largest group with 16 countries and greater differences between its members, suggesting greater diversity in their levels of innovation. This group includes countries with developing or emerging economies and a variety of innovation capabilities. The countries in this cluster include Chile, Slovenia, Slovakia, Spain, Estonia, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Mexico, Poland, Portugal, the Czech Republic and Turkey.

The results of the ANOVA (see Table 6) suggest significant differences between clusters in all analyzed dimensions. The high significant *F* values in the three components suggest that the differences between the clusters are statistically significant and that the groups can be distinguished in terms of "Institutional environment and creativity," "Infrastructure and capital for innovation" and "Sustainability and diffusion of knowledge."

Table 6. ANOVA

		Sum of squares	*gl*	*Quadratic mean*	*F*	*Sig.*
Institutional environment and creativity	Between groups	24.590	2	12.295	38.977	.000
	Within groups	10.410	33	.315		
	Total	35.000	35			
Infrastructure and institutional creativity	Between groups	16.522	2	8.261	14.753	.000
	Within groups	18.478	33	.560		
	Total	35.000	35			
Sustainability and diffusion of knowledge	Between groups	9.922	2	4.961	6.528	.004
	Within groups	25.078	33	.760		
	Total	35.000	35			

Source: prepared by the authors.

Next, a *K*-means analysis is performed, which provides a robust and meaningful classification of countries based on their profiles in the dimensions of Institutional Environment and Creativity, Infrastructure and Capital for Innovation and Sustainability and Diffusion of Knowledge. This partitioning method divides the sample of countries into three distinct groups, each with a unique pattern of performance on the key variables of the 2023 GII.

Three clusters were selected for analysis, representing different levels of innovative performance among the countries analyzed. The final centers of the clusters, representing the average value of the countries' scores for the three variables considered, reveal different patterns of innovation capabilities and trends (see Table 7).

Table 7. Final cluster centers

	Cluster		
	1	2	3
Institutional environment and creativity	.26951	.78015	-.86963
Infrastructure and capital for innovation	1.02763	-.58531	-.57739
Sustainability and diffusion of knowledge	.28354	-.90503	.41264

Source: prepared by the authors.

Each cluster is described below based on the final cluster centers:

- Cluster 1: This group is characterized by above-average performance across all evaluated dimensions. In terms of Institutional environment and creativity, it scores 0.26951, indicating an environment conducive to innovation. It particularly stands out regarding Infrastructure and capital for innovation, with an outstanding score of 1.02763, suggesting a solid foundation for developing new ideas. In the area of Sustainability and diffusion of knowledge, it performs slightly above average, with a score of 0.28354.
- Cluster 2: This group has a mixed profile with marked strengths and weaknesses. It stands out significantly in Institutional Environment and Creativity, leading the three clusters with a score of 0.78015. However, it shows deficiencies in the other two dimensions. It ranks below average in Infrastructure and capital for innovation with a score of -0.58531 and has the lowest performance of the three groups in Sustainability and diffusion of knowledge with a score of -0.90503.
- Cluster 3: This group shows a contrasting profile. It performs the worst in Institutional Environment and Creativity with a score of -0.86963 and is below average in Infrastructure and Capital for Innovation with a score of -0.57739. However, it stands out positively in Sustainability and diffusion of knowledge, exceeding the average with a score of 0.41264. This indicates a particular strength in these areas, despite weaknesses in other departments.

In summary, each cluster represents a group of countries with specific characteristics regarding innovation and development. Cluster 1 stands out in all dimensions, especially Infrastructure and capital for innovation. Cluster 2 stands out in Institutional environment and creativity but has deficiencies in Infrastructure and sustainability. Cluster 3 has difficulties in Institutional environment and Infrastructure but shows strength in Sustainability and diffusion of knowledge.

5. DISCUSSION

The results of the exploratory factor analysis provide robust empirical validation for the proposed conceptual framework of innovation ecosystems. Identifying three latent dimensions that explain 69.651% of the total variance confirms the multidimensional structure theorized for innovation ecosystems. This aligns with the propositions of Huang *et al.* (2023) regarding the complex and multifaceted nature of these systems.

Dimension 1 (Institutional environment and creativity) effectively operationalizes Schumpeter's creative destruction and North's (1990) institutional framework concepts. The concentration of institutional, regulatory and digital creativity variables in this dimension (factor loadings > 0.68) confirms that effective innovation ecosystems require solid institutional foundations to facilitate experimentation and economic renewal.

Principal component analysis reveals that this first dimension has the greatest explanatory power (36.331% of the variance), suggesting its catalytic role in innovative ecosystems. The high factor loadings of institutional environment (0.920), business environment (0.857) and online creativity (0.839) empirically confirm the institutional theory, which states that formal and informal institutions provide the fundamental social infrastructure for innovative activity.

This dimensional concentration is consistent with the literature on national innovation systems (Freeman, 1987; Lundvall, 1992), which emphasizes that institutional quality determines incentives for investment in research and development (R&D) and entrepreneurial risk-taking. Countries with high scores in this dimension (cluster 2) exhibit environments conducive to technological experimentation and creativity, validating theoretical propositions about the role of institutions in facilitating innovation.

Complementing this finding, the second dimension (18.750% of the variance) operationalizes the material and financial input needed to translate institutional capabilities into innovative products. The significant burdens of market diversification (0.839), intangible assets (0.732) and innovation and development (0.705) confirm Romer's (1990) endogenous growth theory. This theory states that the accumulation of physical, human and technological capital generates increasing returns on innovation.

The distribution of countries in this dimension reveals relevant interpretative patterns. Cluster 1 has the highest score (1.02763), indicating that innovation leaders have achieved balanced configurations between institutional capabilities and material resources. This empirical convergence supports Chesbrough's (2003) propositions on open innovation, which state that the availability of resources facilitates the integration of external knowledge with internal capabilities.

The third dimension (14.570% of the variance) captures mechanisms for transferring and sustainably applying innovative knowledge. This dimension groups diffusion of knowledge (0.794), ecological sustainability (0.782) and creativity in goods and services (0.744). Empirically, this confirms that advanced ecosystems integrate sustainability considerations into their innovation processes, validating emerging trends in literature on green innovation and the circular economy.

This dimension is particularly revealing in that cluster 3 (emerging innovation countries) has the highest score (0.41264), suggesting that these countries have developed comparative advantages in sustainable diffusion mechanisms. This may be a strategy to differentiate themselves in the face of limitations in traditional infrastructure.

The resulting empirical typology confirms the existence of different models of innovative ecosystems within developed economies. The 14 countries in cluster 1 (including Germany, the United States, Sweden and Switzerland) represent the archetype of mature ecosystems that have balanced configurations across all three dimensions. Their empirical characteristics validate Lundvall's (1992) theoretical model of national innovation systems, in which synergistic interaction between institutions, resources and infrastructure generates superior innovative capabilities.

The multidimensional profile of these countries confirms Moore's (1993) propositions on business ecosystems, where the coevolution of multiple actors generates sustainable competitive advantages. Their high score in infrastructure and capital (1.02763) combined with superior performance in the other dimensions, suggests that these countries have developed virtuous circles, where strengths in one dimension reinforce capabilities in others.

The six countries in cluster 2 show a pattern of specialization in the institutional environment (0.78015) but have relative limitations in infrastructure (-0.58531) and sustainability (-0.90503). This configuration suggests ecosystems with advanced institutions that are unable to fully translate these advantages into material infrastructure or sustainable dissemination mechanisms.

This typology is theoretically relevant because it challenges linear conceptions of ecosystem development while suggesting that different countries can follow specialized trajectories based on their comparative institutional advantages.

The empirical pattern is consistent with the literature on varieties of capitalism (Hall and Soskice, 2001), which establishes that different institutional configurations can generate specific competitive advantages.

The sixteen countries in cluster 3 exhibit the most heterogeneous pattern, with institutional (-0.86963) and infrastructural (-0.57739) limitations, but strengths in sustainability and dissemination (0.41264). Theoretically, this pattern is consistent with technological catch-up models (Lee and Lim, 2001) in which countries with resource constraints develop specialized capabilities in absorbing and adapting external technologies. The relative strength in sustainability suggests that these countries may be developing competitive advantages in green innovation and clean technology sectors.

This research confirms that innovative ecosystems are complex multidimensional phenomena that cannot be adequately captured by one-dimensional approaches or isolated indicators. The identified factor structure validates theoretical propositions about the systemic nature of innovation, wherein interactions between institutions, infrastructure and diffusion mechanisms generate emergent properties.

6. CONCLUSIONS

The research empirically demonstrates that innovative ecosystems in OECD countries are structured according to three differentiated latent dimensions. This provides quantitative validation to conceptual frameworks that previously lacked robust empirical foundations. Identifying specialized configurations within developed economies challenges the idea that national innovation systems are homogeneous, suggesting the need for theoretical frameworks that incorporate multiple trajectories of innovative development.

The most significant finding is the analysis is the empirical emergence of sustainability as a constitutive dimension of contemporary innovative ecosystems. This finding suggests a transformation in the conceptualization of innovation systems, in which environmental considerations are structurally integrated rather than treated as externalities. This theoretical evolution requires conceptual refinement to capture the transition toward sustainable innovation models in advanced economies.

These theoretical findings have important practical implications for designing public policy. The results provide empirical foundations for designing differentiated innovation policies according to specific types of ecosystems.

Leading countries (cluster 1) require strategies to maintain their competitive advantages and global technological leadership. Countries with institutional specialization (cluster 2) need policies that translate regulatory strengths into material infrastructure and dissemination mechanisms. Countries with emerging capabilities (cluster 3) can benefit from strategies that capitalize on their strengths in sustainability and knowledge diffusion.

The research showed that international collaboration should consider areas of complementarity between specializations. The findings suggest that strategic alliances between clusters can generate synergies where countries with institutional strengths (cluster 2) collaborate with countries specializing in sustainable dissemination (cluster 3), thus facilitating the two-way transfer of capabilities.

The research confirms that innovative ecosystems are complex multidimensional phenomena that cannot be adequately captured by one-dimensional approaches or isolated indicators. The identified factor structure validates theoretical propositions about the systemic nature of innovation, in which interactions between institutions, infrastructure and diffusion mechanisms generate emergent properties.

Finally, the research contributes to the understanding that national innovative competitiveness does not result solely from the accumulation of resources but rather from the strategic configuration of complementary capabilities that generate synergies. This general perspective provides the theoretical foundation for designing more effective, contextually appropriate innovation policies.

However, it is important to recognize the inherent limitations of this study, which contextualize the interpreting of its results. Although the focus on OECD countries is methodologically justified, it limits the generalization of findings to other contexts. Comparative studies that include emerging and developing economies would allow us to identify patterns of convergence or divergence in the evolution of global innovative ecosystems.

One promising avenue of research involves analyzing specific mechanisms that facilitate transitions between typologies in order to understand the processes by which countries in cluster 3 can evolve toward cluster 1 configurations or how countries in cluster 2 can develop infrastructure capabilities. This would provide valuable insights for designing ecosystem development policies. Future lines of research along these lines would contribute significantly to the theoretical and practical refinement of innovative ecosystem studies.

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