Journal of Applied Economic Sciences
Volume XX, Winter, Issue 4(90), 2025

Decoding National Genius: Efficiency of Intellectual Capital Utilisation in the European Union

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Article's history:
Received 5th of November, 2025; *Revised* 9th of December, 2025; *Accepted* 22th of December, 2025; *Available online*: 30th of December, 2025. *Published* as article in the Volume XX, Winter, Issue 4(90), December, 2025.

Suggested citation:
Slyvkanych, N. (2025). Decoding National Genius: Efficiency of Intellectual Capital Utilisation in the European Union. *Journal of Applied Economic Sciences*, Volume XX, Winter, 4(90), 875 – 894. https://doi.org/10.57017/jaes.v20.4(90).14

Abstract:
This study examines the efficiency and development of National Intellectual Capital (NIC) among European Union (EU) member states from 2000 to 2022. Utilising a Data Envelopment Analysis (DEA) approach, the research assesses the effectiveness with which countries convert Human Capital (HC), Structural Capital (SC), and Relational Capital (RC) into innovative and economic outcomes, such as GDP per capita and the Global Innovation Index. The findings indicate both temporal convergence and regional disparities in NIC efficiency. Over the period, most EU countries have enhanced their capacity to utilise intellectual capital, resulting in increased homogeneity and resilience within the union. Regional differences persist: Northern and Western Europe, particularly Scandinavia, the Benelux, and parts of Western Europe, exhibit high DEA scores, indicating advanced innovation and robust institutions. Southern and Eastern Europe have lower efficiency due to issues related to education, research and development, and institutional factors. The study highlights Structural Capital's role in sustaining innovation efficiency, identifies Human Capital as the most adaptable and policy-sensitive component, and confirms that EU policies have gradually aligned national intellectual capital performance across member states.

Keywords: national intellectual capital; human capital; structural capital; relational capital; data envelopment analysis.

JEL Classification: C61; O15; O31; O34; E01.

Introduction

National wealth, competitiveness, and economic growth are key concerns for leaders, policymakers, and global organisations. Consequently, various national rankings, such as the World Competitiveness Yearbook by the International Institute for Management Development (IMD), have garnered attention. The Organisation for Economic Cooperation and Development (OECD) also assesses and forecasts the future wealth of its member countries. These rankings help national leaders understand their country's position globally, identify benchmark nations, and develop effective strategies to enhance national development and competitiveness.

Over the past few decades, intangible assets, such as knowledge, patents, and innovation, have been recognised as fundamental sources of wealth and progress (Lin & Edvinsson, 2011). In today's economy, driven by knowledge, intellectual capital is vital for a nation's competitiveness and sustainable growth. Managing intangible assets, such as Human, Structural, and Relational Capital, is key to a country's ability to innovate and adjust to economic changes. Together, these components form National Intellectual Capital (NIC), reflecting a country's capacity to develop, disseminate, and utilise knowledge for both economic and social progress.

Within the European Union (EU), enhancing the efficiency of intellectual capital has been a key strategic objective through initiatives such as the Lisbon Strategy, Europe 2020, and Horizon 2020. The Lisbon Strategy aimed to make the EU "the most competitive knowledge-based economy in the world, "while the Europe 2020 strategy focuses on achieving innovative, sustainable, and inclusive growth. Both strategies emphasise that economic development relies heavily on knowledge and intellectual capital (Jednak et al., 2017). However, substantial differences still exist among member states in education results, innovation ability, and institutional efficiency. It is crucial to understand how well EU countries transform their intellectual resources into concrete outcomes to tackle regional disparities and foster unified growth.

This research employs Data Envelopment Analysis (DEA) to systematically assess the efficiency of National Innovation Capabilities (NIC) utilisation among European Union member states over the period spanning 2000 to 2022. By integrating Human Capital (HC), Social Capital (SC), and Research Capital (RC) as input variables, and utilising Gross Domestic Product (GDP) and the Global Innovation Index as output indicators, the analysis encompasses both temporal and spatial dimensions of intellectual capital efficiency. The findings elucidate two predominant patterns: (1) a general temporal convergence characterised by widespread improvements across nations, and (2) a persistent spatial disparity wherein Northern and Western European countries consistently outperform their Southern and Eastern counterparts in the cultivation and application of intellectual capital. These results contribute to the extant scholarly discourse on the EU's knowledge economy and underscore critical areas for targeted policy implementation.

1. Literature Review

The term "intellectual capital" was first used by John Kenneth Galbraith in his pioneering work in 1969 (Pedro et al., 2018). Some later definitions referred to intellectual capital as the difference between the accounting and market value of an organisation (Stewart & Losee, 1994). Later, Edvinsson & Malone (1997) defined intellectual capital as knowledge that can be converted into economic value. The importance of intangible assets and intellectual capital was also emphasised by innovation and management theorists such as Schumpeter (1983) and Drucker (1954, 1985). Significant attention to the topic of IC was devoted from the early 1990s, when intellectual capital began to be understood as non-material capital and part of the knowledge economy (Manzari et al., 2012).

Studies in the field of intellectual capital research have identified a taxonomy of four phases (Dumay & Gagarina, 2012; Guthrie et al., 2012; Labra & Paloma Sánchez, 2013; Roos & O'Connor, 2015). In Table 1, we provide a brief description of the basic characteristics of each temporal stage.

Table 1: Taxonomy of the four stages of intellectual capital

Stage	Period	Research focus and direction
1st Stage: Development of a theoretical framework	The late 1980s to 1990s	Focus: organisational intellectual capital. Intellectual capital focused on realising its importance in creating and managing sustainable competitive advantage.
2nd Stage: Development supported by empirical evidence	2000 - 2003	Focus: organisational intellectual capital. Approaches to measuring and managing intellectual capital are demonstrated, justified, and supported by empirical evidence. The conceptualisation of specific aspects of intellectual capital began (such as incorporation into accounting, management, reporting, and measurement of IC). Various classifications were created to help define and categorise different methods of measuring and evaluating intellectual capital.
3rd Stage: Development of research into the consequences of using intellectual capital	2004 - Present	Focus: organisational intellectual capital. Practical analysis with deeper utilisation of intellectual capital management (based on decisions according to the type of company).

Stage	Period	Research focus and direction
4th Stage: Development of regional and national intellectual capital	2004 - Present	Focus: national and regional IC. Research into intellectual capital within the context of ecosystems at the national and regional levels. A shift in approach to understanding the drivers of wealth creation, which are based on a balance of intellectual and financial measures. These approaches aim to create a more holistic vision of national innovative capacity and to inform policies and society. This stage aligns with current research in the field of intellectual capital, incorporating the latest scientific findings.

Source: own processing according to Pedro et al. (2018)

Organisational intellectual capital comprises the intangible resources within an organisation, including knowledge, information, and intellectual property derived from both human and technological assets. It serves as a potential source for generating value for all stakeholders and provides a sustainable competitive edge (Bontis, 2002; Brooking, 1997; Edvinsson & Malone, 1997; Lev, 2018; Roos & Roos, 1997; Youndt et al., 2004).

Regional intellectual capital consists of resources within a region, such as knowledge, information, and intellectual property from individuals, organizations, communities, and places. These resources support the region's economic growth, human development, sustainability, and quality of life. (Bradley, 1997; Edvinsson & Stenfelt, 1999; Ren, 2008; Schiuma & Lerro, 2008).

National intellectual capital is a combination of a country's intangible assets, encompassing all types of knowledge, information, and intellectual property from individuals, organisations, and regions. These resources help generate wealth and support the country's economic growth, alongside human development, sustainability, and quality of life. (Bontis, 2002; Corrado et al., 2005; Marinelli et al., 2022).

In developed countries, economic development is primarily based on knowledge. Traditional factors such as land, labour, and capital are no longer the primary sources of growth; however, these factors remain dominant in developing countries. Due to rapid technological changes, developed nations have shifted their focus to the service sector, whereas developing countries continue to concentrate on agriculture and manufacturing. These sectors do not provide high-value-added output, higher employment, productivity, income, or improved living standards. To advance their development, developing countries should adopt practices, capital, and technologies from developed nations and build strong institutions. Since domestic capital is often insufficient, foreign investment plays an important role in their economic growth. Additionally, developing countries should align with the European Union and the global economy by fostering a knowledge-based economy. This involves investing in education, research, development, and advanced technologies to promote innovation, which in turn enhances productivity, income, and living standards. However, this progression is not feasible for all developing nations due to limited capital, savings, and external financing sources. Currently, investments primarily target traditional factors and sectors, including land, labour, agriculture, and industry (Jednak et al., 2017).

2. Research Methodology

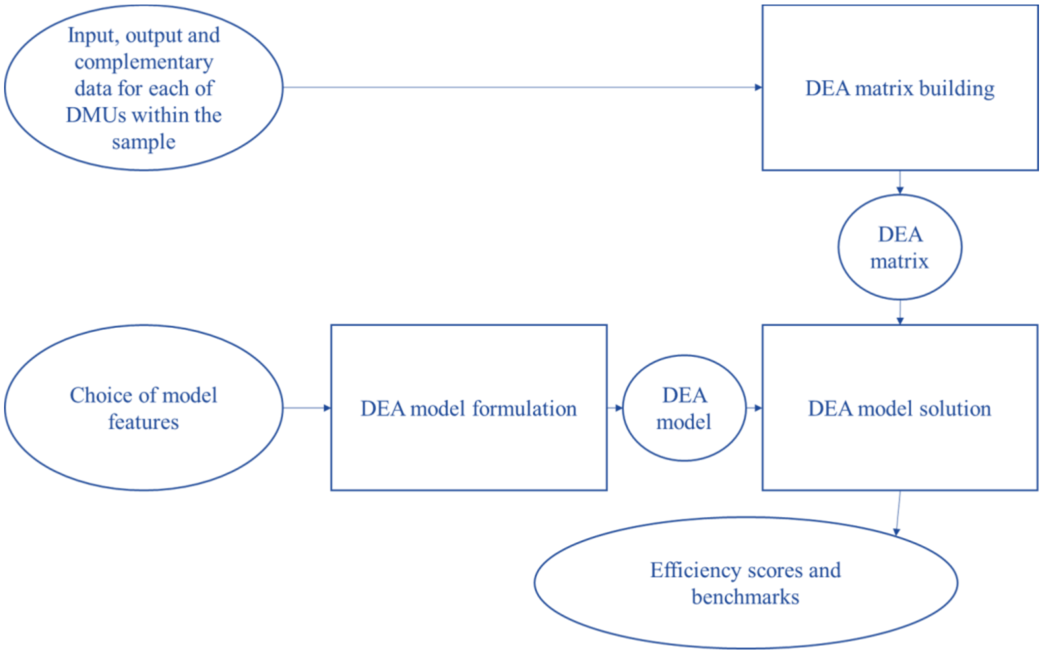
As the primary methodological approach, we employ Data Envelopment Analysis (DEA) as an alternative valuation technique, which relies on linear programming procedures and applies to a broad spectrum of evaluation challenges (Nitkiewicz et al., 2014). DEA is a method developed by Charnes et al. (1978) that measures the efficiency of units (e.g., institutions, firms, or counties), called Decision-Making Units (DMUs), by looking at multiple inputs and outputs without assuming a specific production process. This method works well for analysing across very different settings, such as various countries, legal systems, or economic backgrounds (Cooper et al., 2007; Martín-Gamboa & Iribarren, 2021).

Two main DEA models are identified: the CCR model (Charnes et al., 1978), assuming constant returns to scale, and the BCC model (Banker et al., 1984), which assumes variable returns to scale. Due to the varied economic contexts across the global sample, this study uses the input-oriented VRS (BCC) model, allowing for efficiency differences arising from scale effects. The input-focused approach is suitable because firms aim to minimise their intellectual capital inputs to achieve a certain level of performance. For each country j, the DEA model is formulated as follows:

$$\min_{\theta,\lambda}\theta \qquad \text{subject to:} \qquad Y\lambda \geq Y_j, \theta X_j \geq X\lambda, \lambda \geq 0, e'\lambda = 1,$$

where: X and Y represent the inputs and outputs across the countries, λ is a vector of intensities, θ is the efficiency score (⟨0;1⟩) and e is a vector of ones. If the country is considering efficient (θ=1) it means that the country operates on the efficiency frontier.

Figure 1: Data envelopment analysis



Source: own processing according to Martín-Gamboa & Iribarren (2021)

The DEA methodology outlined above provides insights into the relative efficiency of decision-making units (DMUs). Typically, DMUs evaluated with DEA are assumed to be homogeneous, operating within the same environment. Analysing how contextual variables influence efficiency has become a key focus in DEA research. Banker et al. (2019) offers an overview of two-stage DEA applications. Generally, in the first stage, DEA software calculates efficiency scores based on input and output data. In the second stage, these scores are regressed against relevant contextual variables to determine which factors significantly affect performance and to assess their influence (see, e.g., Amundsveen et al., 2014; Coelli et al., 2005; Hoff, 2007; Simar & Wilson, 2011; Zhang et al., 2024). There are two primary uses of this second-stage analysis: one is to understand which factors positively influence efficiency, and the other is to adjust for their effects. Yet, the most common method to realise the second stage of the DEA approach is OLS, but the authors recommend, as a direction for further research, extended techniques such as Tobit Regression, Factorial Logistic Regression, truncated regression, or convex non-parametric least squares regression (Afsharian et al., 2024; Hoff, 2007; Sklavos et al., 2025; Yadava et al., 2025).

For this purpose, we use three different approaches to provide robust results. As main approaches in the second stage, we use: Ordinary least squares regression (OLS), Tobit Regression (TOBIT) and Fractional regression model (FRM) (Hoff, 2007; Papke & Wooldridge, 1996; Ramalho et al., 2010; Tobin, 1958):

- OLS estimates the linear relationship between the DEA efficiency score $E_i$of DMU and a vector of explanatory variables X_i:

$$E_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + \varepsilon_i,$$

where: ε_i is the error term.

- The Tobit model addresses the censoring of DEA scores at 1 (fully efficient units) by introducing a latent variable E_i^*:

$$E_i^* = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + \varepsilon_i,\ \ \varepsilon_i \sim N(0, \sigma^2).$$

The observed efficiency score is:

$$E_i = \begin{cases} E_i^* & if\ 0 < E_i^* < 1 \\ 0 & if\ E_i^* \geq 1 \\ 1 & if\ E_i^* \leq 0 \end{cases} .$$

- Fractional regression is designed for proportions bounded between 0 and 1 (which makes that approach ideal and highly recommended for DEA). The conditional mean of E_i is modelled as:

$$E(E_i|X_i) = G(X_i\beta) = \frac{\exp(X_i\beta)}{1+\exp\,(X_i\beta)},$$

where $G(\cdot)$ is the logistic function, which ensures predicted values remain in [0,1] and accommodates corner solutions at 0 or 1.

To verify the reliability of the DEA efficiency estimates, several robustness procedures were implemented. First, the analysis employs both constant returns to scale (CRS) and variable returns to scale (VRS) models. The CRS specification provides a benchmark measure of overall technical efficiency under the assumption of proportionality between inputs and outputs, whereas the VRS model relaxes this constraint and captures pure technical efficiency by removing potential scale effects. Comparing the results of the two approaches allows us to assess the sensitivity of country rankings to the assumed production frontier. The close correspondence between the CRS and VRS outcomes indicates that the efficiency scores are not materially affected by scale assumptions, thereby supporting the robustness of the DEA results.

In addition, the temporal properties of the efficiency scores were examined using established convergence metrics from the productivity literature. σ-convergence was assessed by analysing changes in the cross-sectional standard deviation of DEA scores over the study period. A declining level of dispersion suggests increasing similarity among EU member states in their utilisation of national intellectual capital and indicates that the DEA estimates display stable behaviour over time. Complementing this assessment, β-convergence was evaluated through regressions of efficiency growth on lagged efficiency levels. A negative and statistically significant coefficient provides evidence of a catch-up mechanism, whereby initially less efficient countries tend to experience more rapid improvements than their higher-efficiency counterparts. This dynamic pattern reinforces the interpretation that the estimated inefficiencies reflect substantive structural differences rather than random variation.

For the DEA analysis, data were collected from various publicly accessible databases. The variables and their respective sources are detailed in Table 2. Data for EU countries spanning the years 2000 to 2022 were collected to ensure a comprehensive and longitudinal analysis of trends within the European Union over a significant period. This selection period allows for the examination of both short-term fluctuations and long-term developments, providing a robust basis for empirical investigation

Table 2: Collected variables

Variable	Unit of measure	Source	Used Abbreviation
Mean years of schooling	Average number of years	UNESCO	SCHOOL
Gross enrolment ratio, primary to tertiary, both sexes	Percentage of total population	UNESCO	ENROLL
Researchers in R&D	Number of engaged researchers expressed as per million	World Bank	RESEARCHERS
R&D expenditures	Percentage of GDP	World Bank	RD
Internet users (ICT access)	Percentage of population	World Bank	ICT
Institutional quality (Government Effectiveness)	Percentile ranking (0 – 100)	World Bank	INSTITUTION
Trade openness	Percentage of GDP	World Bank	TRADE
FDI inflow	Percentage of GDP	World Bank	FDI
High-tech exports	Percentage of total exports	World Bank	HI_TECH
GDP per capita	Percentage of annual growth	World Bank	GDP
Global innovation index	Percentile score (0 – 100)	WIPO	GII

Source: own processing

All collected variables were normalised using the min-max normalisation approach as follows:

$$X_i' = \frac{X_i - \min(X)}{\max(X) - \min(X)},$$

where X_i' is a normalised variable, X_i is the original variable for country i, $\min(X)$ and $\max(X)$ are the minimum and maximum of that variable across the sample. This transformation ensures that all variables lie within the interval ⟨0,1⟩, preserving the proportional differences between observations while eliminating the effect of measurement units.

Using the normalised variables, we calculated the national intellectual capital and its components as follows:

$$HC = \frac{1}{n}\sum_{i=1}^{n} X_i',$$

where HC is Human Capital, and for its calculation, we use the following variables: mean years of schooling, enrolment ratio, and researchers in R&D.

$$SC = \frac{1}{n}\sum_{i=1}^{n} X_i',$$

where SC is Structural Capital, and for its calculation, we use variables: R&D expenditures, Internet users (to measure ICT access), and institutional quality.

$$RC = \frac{1}{n}\sum_{i=1}^{n} X_i',$$

where RC is Relational Capital, and for its calculation, we use variables: trade openness, FDI inflows, and hi-tech exports.

The overall calculation of National Intellectual Capital is:

$$NIC = \frac{HC+SC+RC}{3}.$$

To explore how efficient countries use their intellectual capital, we divide our variables to input and output variables as follows:

- Input: Human Capital, Structural Capital and Relational Capital;
- Output: Gross Domestic Product and Global Innovation Index.

3. Case studies

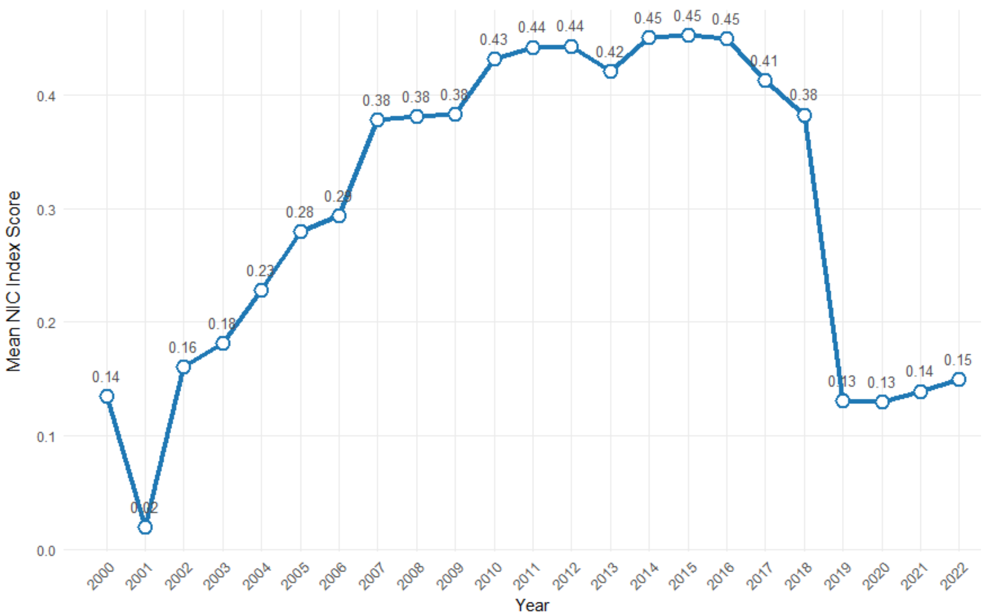
Table 3 presents key descriptive statistics for the variables analysed. It reveals considerable variation in intellectual capital components among countries and over time. Human Capital (HC) varies from -0.73 to 0.84, reflecting significant differences in human resource efficiency and development. Structural Capital (SC) has an average of 0.53, indicating that most countries possess robust structures for knowledge creation. Relational Capital (RC) has a mean of 0.27 with the smallest standard deviation (SD = 0.10), suggesting more consistent management of external relationships. For macroeconomic factors, GDP growth shows variability indicating differing economic conditions. The Global Innovation Index ranges highlight global disparities in innovation. Overall, these variable variations justify the use of the DEA method and further analysis to evaluate efficiency and performance differences.

Table 3: Descriptive statistics of inputs and outputs

Variable	Min	Mean	Max	SD
HC	-0.73	0.10	0.84	0.43
SC	-0.22	0.53	0.94	0.24
RC	0.13	0.27	0.79	0.10
GDP	-14.64	2.35	23.44	4.04
GII	-1	9.16	64.80	7.98

Source: own processing

Figure 2: Evolution of the composite National Intellectual Capital (NIC) Index

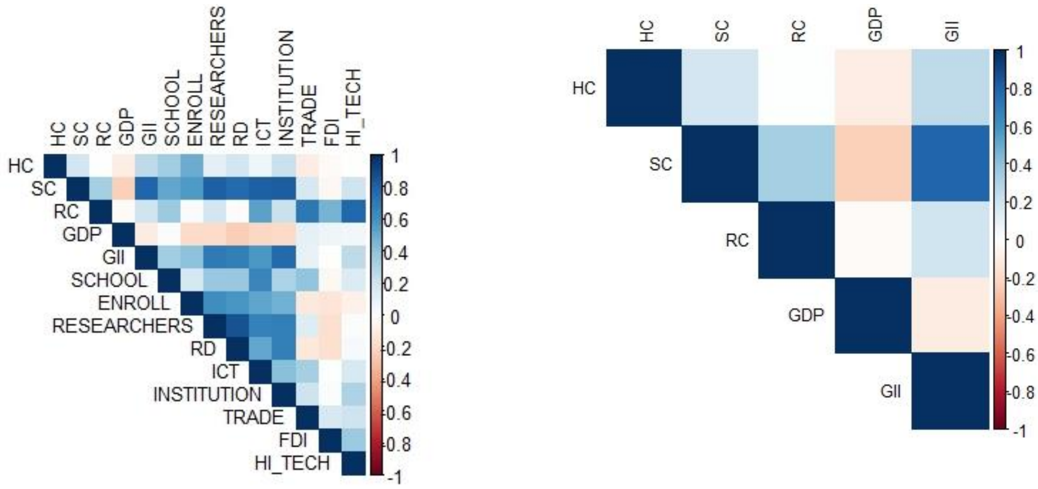


Note: using the mean NIC Index score across all countries over the selected period
Source: own processing

The decline in the Composite National Intellectual Capital (NIC) Index observed in Figure 2 after 2016 can be attributed to several global disruptions. Economic slowdown, trade tensions, and reduced investment in education and innovation weakened the formation of intellectual capital. The sharp drop after 2019 likely reflects the impact of the COVID-19 pandemic, which disrupted human capital development, research activities, and international collaboration. Additionally, geopolitical instability and wars, such as the Russia–Ukraine conflict, further constrained knowledge flows and innovation systems, leading to a notable decline in global intellectual capital.

To examine the correlation between variables, we use a correlation matrix illustrated in Figure 3 (correlation for the general sample on the left and input-output correlation on the right).

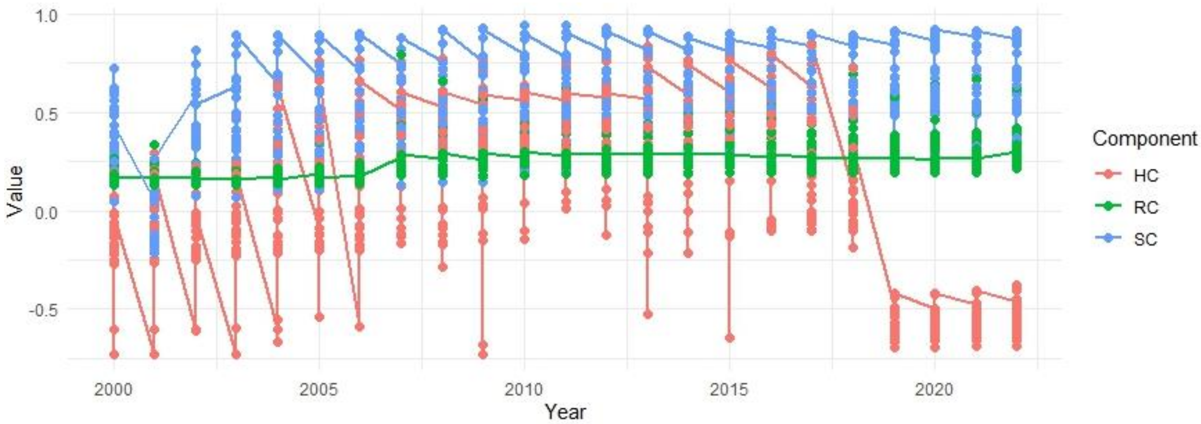
Figure 3: Evolution of the composite National Intellectual Capital (NIC) Index



Source: own processing

Figure 4 illustrates the temporal evolution of the three components of the National Intellectual Capital (NIC) within the European Union over the period from 2000 to 2022. The observed trends suggest a consistent hierarchy among these components, with Structural Capital (SC) maintaining the highest and most stable levels. This pattern indicates a sustained commitment by the EU to invest in research and development, information and communication technologies, and institutional capacity, elements that are fundamental to fostering innovation and enhancing productivity.

Figure 4: Evolution of NIC components

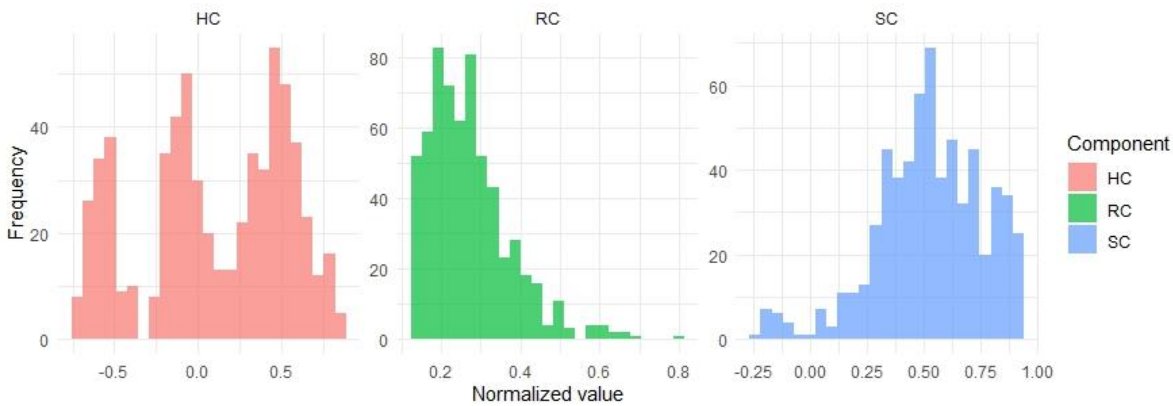


Source: own processing

Relational Capital (RC) exhibits moderate and relatively stable levels, consistent with the EU's ongoing process of integration and its open trade policies. Small increases in RC correspond to periods of heightened intra-EU trade and foreign direct investment inflows, indicating a resilient and interconnected external innovation network. Conversely, Human Capital (HC) demonstrates considerable fluctuation over time. The upward trajectory noted in the early 2000s aligns with advancements in educational attainment and increased tertiary enrolment rates. Conversely, the decline observed after 2015 appears to be influenced by demographic shifts, skill mismatches, and disparities in educational quality among member states. This pronounced variability underscores HC as the most dynamic and policy-sensitive element of NIC within the European Union framework. Overall, the results highlight that while SC and RC offer a stable foundation for the EU's knowledge economy, HC remains the key constraint and potential lever for boosting long-term intellectual capital accumulation and innovation capacity.

Figure 5 shows the distribution of the three main parts of National Intellectual Capital (NIC) across European Union countries: Human Capital (HC), Relational Capital (RC), and Structural Capital (SC). Each part has been standardised to make comparison easier and to examine differences in their spreads and possible effects on overall intellectual capital efficiency. The distribution of Human Capital (HC) reveals a bimodal pattern, with two clear peaks around negative and moderately positive normalized values. This indicates a division among EU member states regarding human capital development, with some countries showing below-average levels—possibly due to lower educational attainment, skill shortages, or limited investment in lifelong learning—while others reach higher levels, reflecting strong educational systems and a more skilled workforce. The Relational Capital (RC) component has a right-skewed distribution, with most values between 0.2 and 0.4. This shows that, although some countries have fairly strong external ties and trust-based networks, most display moderate to low levels of relational capital. Structural Capital (SC) exhibits a left-skewed distribution, with values mainly between 0.5 and 0.8. This suggests that many EU countries have relatively advanced institutional and infrastructural frameworks that support innovation and knowledge management.

Figure 5: Distribution of NIC components



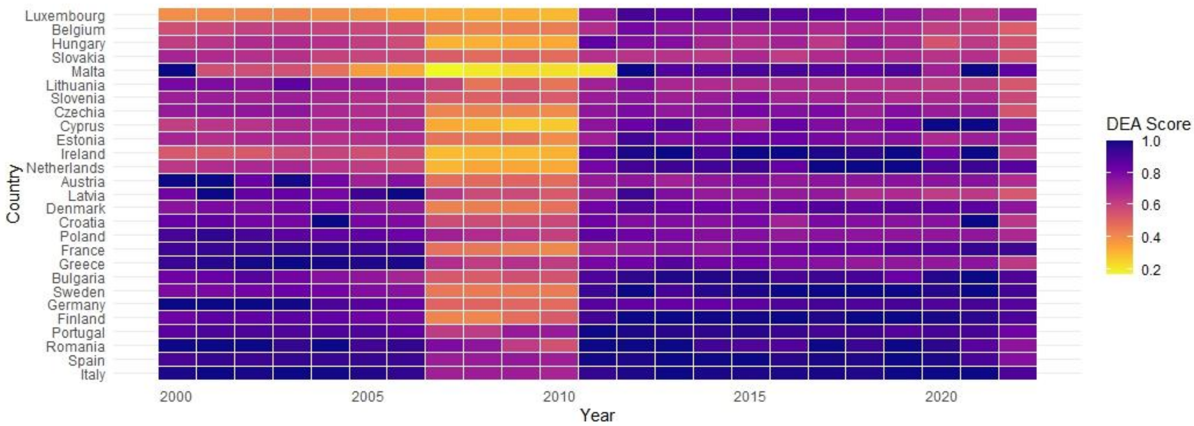
Source: own processing

Figure 6 illustrates how DEA efficiency evolved among EU member states from 2000 to 2022, highlighting clear temporal and geographic patterns in the use of national intellectual capital (NIC). In the early 2000s, efficiency was uneven, with Western and Northern European nations like Luxembourg, Belgium, and the Netherlands typically outperforming newer Central and Eastern European members. This initial gap indicates ongoing structural and institutional changes in post-transition economies and their slow integration into the EU innovation system.

Between 2005 and 2010, a clear convergence trend is evident. Newer members such as Slovakia, Hungary, Lithuania, and Malta show significant efficiency improvements, aligning with their EU accession and the absorption of structural and cohesion funds. Enhancements in R&D investments, educational systems, and policy harmonization played a role in boosting intellectual capital efficiency. Between 2010 and 2015, DEA efficiency across several member states shows a brief period of stagnation or slight decline, indicating the lingering impact of the global financial crisis and subsequent fiscal consolidation. During this time, countries' ability to convert R&D spending and human capital investments into productive and innovative results was temporarily limited. After 2015, efficiency scores across EU countries became more similar, reflecting the overall development of the Union's knowledge and innovation systems. Most member states sustained medium-to-high efficiency ratings, implying enhanced institutional capacity and better resource management through initiatives like Europe 2020 and Horizon 2020. By the conclusion of the 2020–2022 observation period, DEA efficiency remains fairly stable and resilient, even in the face of external challenges like the COVID-19 pandemic. This indicates that the EU's sustained focus on research collaboration, digital infrastructure, and institutional integration has helped develop a more balanced and adaptable innovation ecosystem, reducing disparities between early and late EU members while maintaining overall intellectual capital efficiency.

These efficiency patterns align with earlier observations in the NIC components. Specifically, countries with high DEA efficiency generally show robust and steady Structural Capital (SC) performance, while variations in Human Capital (HC) are closely linked to efficiency drops. The relative consistency of Relational Capital (RC) seems to have bolstered overall resilience, indicating that the post-2015 convergence in DEA scores signifies a gradual harmonisation of human and structural capabilities throughout EU member states.

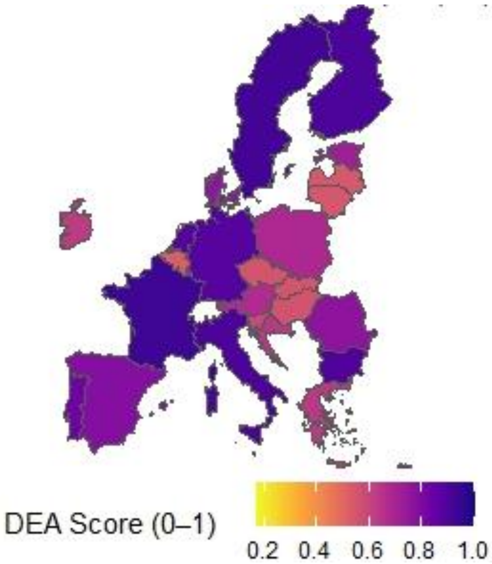
Figure 6: DEA Efficiency evolution across the countries



Source: own processing

Figure 7 displays the DEA efficiency scores for how EU countries utilise their National Intellectual Capital (NIC). Scores range from 0 (least efficient) to 1 (most efficient), reflecting each country's effectiveness in converting intellectual capital inputs into productive outputs. The map's colour gradient varies from yellow (indicating low efficiency) through orange and magenta (medium efficiency) to dark purple (high efficiency). This progression clearly highlights regional differences in NIC utilisation efficiency. Northern and Western European nations, particularly those in Scandinavia, the Benelux region, and parts of Western Europe, exhibit higher DEA scores, shown by darker purple shades. These regions appear to manage and leverage their intellectual capital more effectively, suggesting mature innovation systems, strong human resources, and well-established institutional support for knowledge-driven activities. Conversely, countries in Southern and Eastern Europe tend to have lower DEA scores, represented by lighter orange and magenta colours. This indicates that these nations face challenges in effectively harnessing their intellectual capital for economic and social benefits. Contributing factors may include weaker innovation systems, less advanced research infrastructure, and lower investment in education and research and development (R&D).

Figure 7: DEA Efficiency across EU countries



Source: own processing

The second stage findings sharpen the narrative about why some countries appear more or less efficient in the DEA framework by linking relative efficiency to observable macro-level determinants. The results of the models used in the second stage are illustrated in Table 4.

Table 4: Economic determinants of DEA efficiency

	TOBIT	FRM	OLS
(Intercept)	0.670***	0.765*	0.669***
INSTITUTION	-0.004***	-0.020***	-0.004***
RD	-0.022	-0.138	-0.021
ICT	0.008***	0.041***	0.008***
TRADE	-0.001***	-0.005***	-0.001***
FDI	0.000	0.001	0.000
HI_TECH	-0.005***	-0.023***	-0.005***
logSigma	-1.688***		
R^2			0.233
R^2 Adj.			0.222
RMSE		0.17	0.17
Std. Errors		IID	Heteroskedasticity-robust

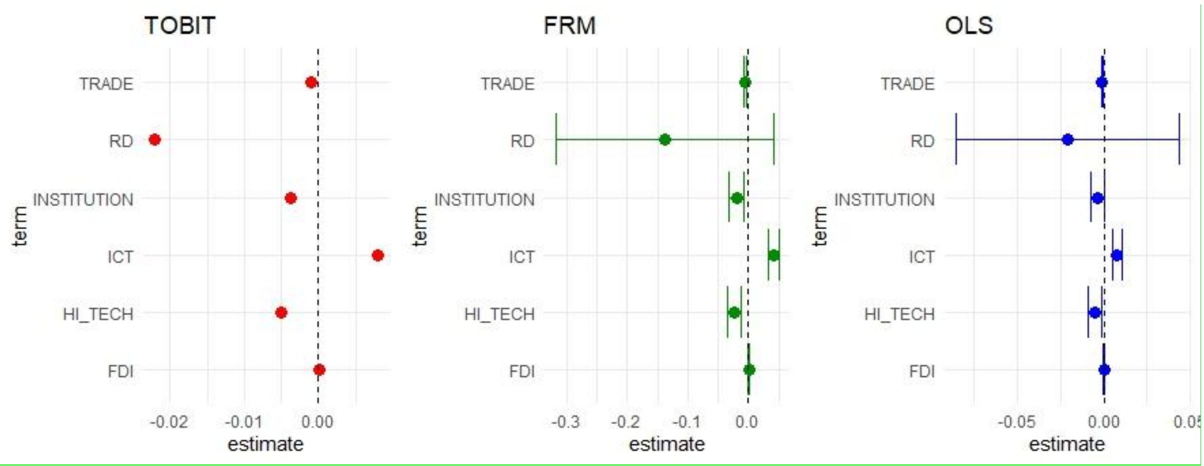
Source: own processing

The strong positive association between ICT and efficiency underscores the significance of digital infrastructure as a universal catalyst for productivity, enabling real-time data exchange, streamlined operations, and cross-border collaboration that bring entities closer to optimal performance levels. This pattern holds particularly true given the widespread adoption of digital technologies across various sectors and regions. The observed negative relationship between Institutional Quality and DEA efficiency requires careful interpretation. While robust institutions are generally linked to superior overall performance, in a cross-country DEA analysis, this may reflect effects related to proximity to the efficiency frontier and measurement nuances.

Countries with high-quality institutions often adopt more detailed reporting, auditing, and control protocols, which can unearth inefficiencies not visible under less rigorous oversight. In essence, the efficiency frontier becomes more stringent in well-governed economies, making it more challenging for individual units to demonstrate significant relative gains within the 0–1 efficiency scale. This does not undermine the value of good governance; rather, it illustrates how the DEA framework highlights both the concealment and exposure of inefficiencies as oversight intensifies. The negative and significant coefficient associated with HI_TECH aligns with the understanding that high-technology, innovative sectors operate on extended development timelines and involve greater process complexity. While these sectors are vital for sustained long-term productivity growth, they often necessitate considerable transformations and capital reallocations before noticeable efficiency enhancements occur, especially in cross-sectional analyses. Accordingly, specialization in high-tech industries may correlate with lower relative efficiency despite delivering high absolute performance in other areas.

Trade openness exerts a modest yet negative impact on efficiency, suggesting that increased openness may prompt reallocation pressures and vulnerability to external shocks, temporarily suppressing efficiency relative to the frontier. Nonetheless, the sign and significance vary across model specifications, indicating a complex interplay between openness, sectoral structure, and national absorptive capacity in shaping efficiency outcomes. FDI demonstrates limited systematic association with efficiency, implying that total inflows alone do not determine proximity to the frontier. The apparent weak link indicates that the impact of FDI depends on its sectoral allocation, integration with local capabilities, and synergy with domestic productivity strategies. Further research could benefit from disaggregating FDI data by sector and host country absorptive capacity to better elucidate the channels through which foreign investment influences efficiency. Similarly, R&D expenditure shows no statistically significant effect, suggesting that at the macro level, aggregate R&D intensity may not directly translate into relative efficiency gains as captured by DEA. This could be due to lag effects, variations in R&D efficiency across countries, or sector-specific dynamics delaying measurable improvements. Recognizing this insignificance emphasizes the importance of assessing both the scale and effectiveness of innovation investments, rather than assuming uniform returns.

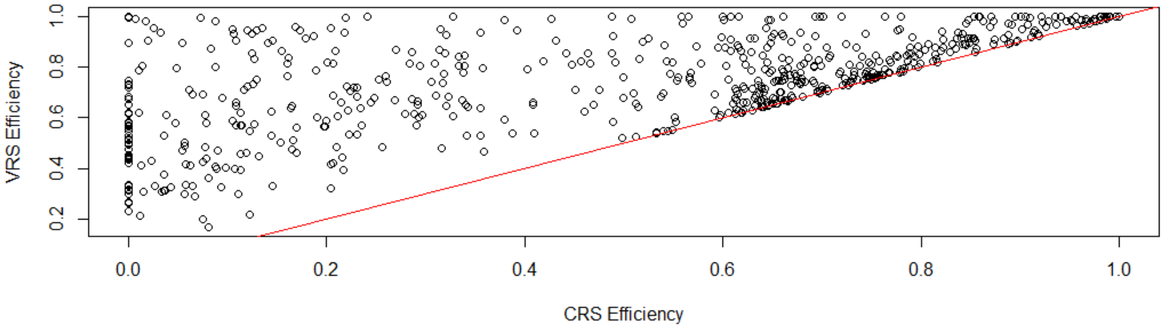
Figure 8: DEA Efficiency scores as a regressor of macroeconomic, institutional and regulatory variables



Source: own processing

To confirm the robustness of the estimated National Intellectual Capital (NIC) efficiency scores, both constant returns to scale (CRS) and variable returns to scale (VRS) models were computed. The comparison reveals a mean CRS efficiency of 0.501 and a mean VRS efficiency of 0.749, indicating that scale-adjusted VRS scores generally identify a higher potential for efficiency gains across EU member states. The correlation between CRS and VRS efficiency scores is 0.639, suggesting a moderate-to-strong consistency in country rankings across the two scale assumptions. CRS–VRS scatterplot (see Figure 9) further validates model robustness: most observations are positioned above the 45-degree line, as theoretically expected, since the VRS frontier envelops the CRS frontier. This confirms that inefficiencies are not driven by scale artefacts but are instead inherent to factor utilisation differences across countries. The choice of the VRS model is therefore justified, as EU countries differ substantially in economic size, factor endowments, and institutional capacities, making variable returns to scale a more realistic representation of the production environment.

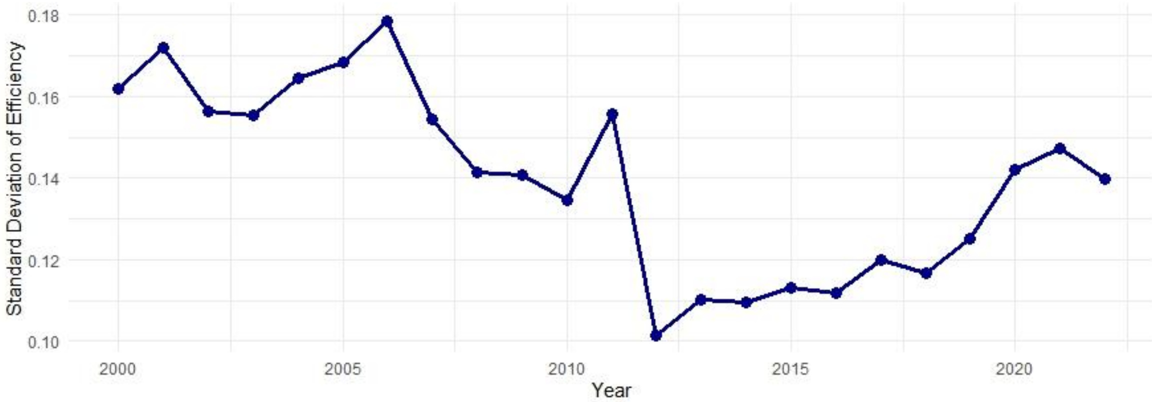
Figure 9: CRS vs VRS DEA Efficiency Scores



Source: own processing

Figure 10 presents the temporal evolution of the standard deviation of VRS DEA efficiency scores for EU member states over the period 1999–2022. The results reveal a pronounced long-term decline in dispersion, albeit with several cyclical oscillations. During the early years (1999 - 2008), cross-country variation remained comparatively elevated (SD ≈ 0.16–0.18). Following the 2008–2009 financial crisis, however, dispersion began a persistent downward trajectory, reaching its lowest point in 2011 (SD = 0.103). While a modest re-divergence is observable after 2018, the overall post-2010 pattern reflects markedly lower variability than in the early 2000s. This downward shift in dispersion is indicative of σ-convergence, suggesting that structural differences in NIC-related efficiency across EU economies have gradually diminished.

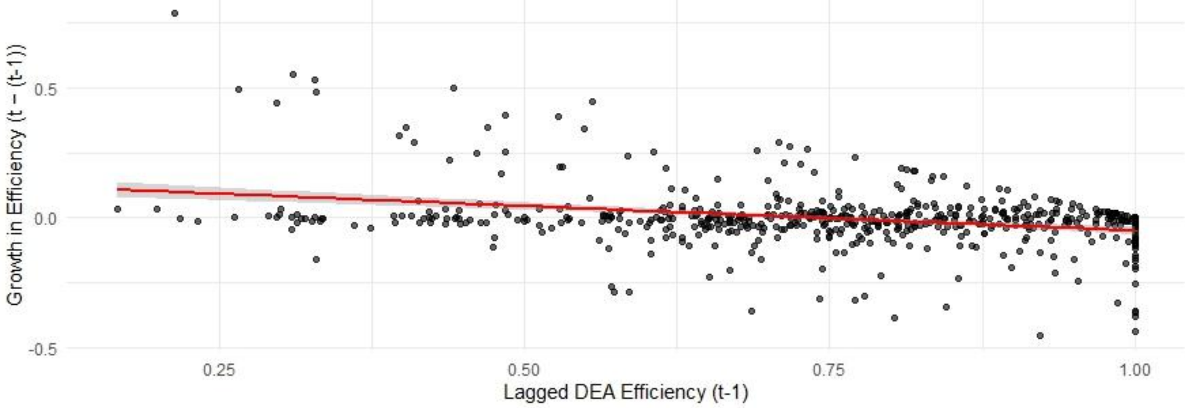
Figure 10: σ-convergence of DEA Efficiency in EU countries



Source: own processing

Figure 11 examines β-convergence by regressing the growth rate of DEA efficiency on its lagged level. The scatterplot and fitted regression line show a negative and statistically significant slope coefficient, implying that countries starting with relatively low NIC efficiency experience stronger subsequent improvements compared to initially high-performing peers. This catch-up effect provides robust evidence of β-convergence in NIC utilisation. The pattern is consistent with broader integration-related processes within the EU, including cohesion policy, targeted R&D harmonisation efforts, and ongoing institutional reforms—particularly within Central and Eastern European member states.

Figure 11: β-convergence of NIC DEA Efficiency in EU countries



Source: own processing

The DEA efficiency results show significant differences in how EU countries leverage their National Intellectual Capital (NIC) to produce socioeconomic benefits. The map reveals a distinct north–south and west–east pattern, with Northern and Western European nations, such as the Nordic countries, the Benelux countries, and parts of Western Europe, demonstrating higher efficiency scores. In contrast, Southern and Eastern European nations perform less effectively. These outcomes correspond with extensive research highlighting structural and institutional disparities in innovation and knowledge-driven growth across the EU (Archibugi & Filippetti, 2018; Crescenzi et al., 2020; Fagerberg & Srholec, 2008).

The regional differences in DEA efficiency mirror longstanding gaps in national innovation systems and the development of intellectual capital. As Lundvall (2016) and Edquist (2013) suggest that nations with advanced systems for learning, innovation, and institutional coordination are better at transforming intangible assets, such as human skills, knowledge networks, and organisational routines — into productive outcomes. The higher DEA scores seen in Northern and Western Europe support this idea: these regions have traditionally invested in education, research, and innovation infrastructure that boost knowledge creation and dissemination (Fagerberg & Srholec, 2008). In contrast, Southern and Eastern EU countries often show weaker systemic coordination and less developed innovation networks. Research by Radosevic & Yoruk (2016) and Krammer (2017) link this to limited R&D spending, fragmented policy execution, and lower absorptive capacity of firms and institutions. Consequently, even when these countries establish physical or institutional frameworks to support innovation, their capacity to convert intellectual capital into tangible efficiency remains limited. Kozuń-Cieślak & Svidroňová (2024) show that post-communist EU member states consistently underperform in transforming innovation inputs into outputs, with Poland and Lithuania recording some of the lowest DEA efficiency levels among the 11 countries examined. Their findings closely mirror the pattern observed in the present study, indicating that inefficiencies in Eastern and Southern Europe are persistent and systemic rather than temporary. This supports the interpretation that structural weaknesses continue to impede the conversion of knowledge assets into productive outcomes.

New findings deepen this understanding by highlighting additional dimensions of intellectual capital that influence efficiency. According to Cabrilo et al. (2024), innovation performance increasingly depends not only on human, structural, and relational capital but also on entrepreneurial capital, trust capital, and renewal capital, particularly when these interact with digital knowledge-management systems. Countries in Northern Europe typically score higher in these emerging dimensions, suggesting a more holistic and modern approach to managing intellectual capital. This may explain why they achieve higher DEA efficiency: they do not merely invest in traditional IC components but also integrate advanced digital and organisational practices that enhance knowledge utilisation.

Institutional and governance factors have a significant influence on DEA efficiency results. Rodríguez-Pose & Di Cataldo (2015) found that regions with better governance, characterised by effective regulation, transparency, and competent administration, tend to perform better in innovation, likewise, Chowdhury et al. (2019) and Balcerzak (2016) highlighted that good institutional quality improves the efficient use of human and relational capital, thereby boosting the utilisation of intellectual capital. The latest DEA data support this trend: nations with stable institutions and strong governance consistently attain higher efficiency scores. The relatively lower DEA performance in several Southern and Eastern European countries can thus be interpreted through the lens of institutional gaps. Weak policy coordination, bureaucratic inefficiencies, and underdeveloped innovation governance have limited their capacity to convert intellectual inputs into economic and technological outcomes (Archibugi & Filippetti, 2018; European Commission, 2023). Recent research reinforces this institutional explanation. Gianelle et al. (2023) demonstrate that the governance quality of regional innovation policy has significant macroeconomic implications across EU regions, with countries exhibiting stronger administrative capacity and coordination mechanisms achieving systematically better innovation and economic outcomes. These findings confirm that governance is not only a complementary factor but a central determinant of how effectively nations transform intellectual capital into measurable results. Thus, institutional weaknesses present in parts of Southern and Eastern Europe likely represent a fundamental constraint on DEA efficiency.

The findings align with previous research emphasising the significance of Human Capital (HC) and Relational Capital (RC) as key factors in enhancing intellectual capital efficiency. Studies by Fagerberg & Srholec (2008) and Crescenzi et al. (2020) indicate that investing in human capital, through education, continuous learning, and skill development, strongly correlates with higher innovation productivity. Likewise, Nahapiet & Ghoshal (1998) and Carayannis & Grigoroudis (2014) highlight relational capital, fostered by trust, collaboration, and inter-organisational connections, as crucial for effective knowledge sharing. Huian et al. (2024), analysing Romanian public research institutes, find that efficient management of human, structural, and relational capital significantly improves the success of technology transfer activities such as patents, licensing, and spin-off creation. As Romania is one of the countries with lower innovation efficiency in the EU, their results demonstrate that specific IC components, and how well they are managed, directly affect the ability of institutions to generate economic benefits from knowledge. These findings suggest that the challenges observed in the DEA analysis are not only national-level problems but also present within organisations operating in lower-performing innovation systems.

DEA results indicate that nations with higher efficiency tend to excel in these areas. For instance, Nordic and Western EU countries feature societies with high trust levels, solid connections between academia and industry, and unified innovation networks, all of which boost social and relational capital. In contrast, countries with lower efficiency frequently have fragmented innovation systems and weaker social capital, which restricts their capacity to utilise structural and human resources effectively (Krammer, 2017; Rodríguez-Pose & Di Cataldo, 2015).

From a policy standpoint, these findings highlight the need for balanced growth in intellectual capital and coherent innovation policies. Simply increasing investment may not lead to better efficiency if institutional coordination, governance, and human resources are weak (Carayannis & Grigoroudis, 2014; OECD, 2021). Therefore, effective policies should focus on:

- Human Capital development should prioritise measures that go beyond general education spending and focus on adaptability and alignment with emerging technological needs. This includes establishing national skills foresight units to coordinate long-term labour-market planning, expanding digital skills and micro-credential systems, and implementing sector-specific upskilling partnerships that embed firms directly into training pipelines. Countries experiencing skilled emigration should introduce STEM talent-return fellowships, tax incentives, and relocation support to rebuild their innovation workforce.
- Strengthening Relational Capital requires deepening the connections between firms, universities, and public institutions. This can be achieved by creating regional knowledge-broker agencies that actively facilitate R&D partnerships, mandating open-innovation requirements in public research grants (e.g., compulsory

industry–university collaboration), and developing digital innovation marketplaces to integrate SMEs into research networks. Such measures enhance trust, collaborative density, and knowledge diffusion—key factors for transforming intellectual capital into measurable innovation outcomes.

- Governance and Structural Capital reforms are essential for ensuring that knowledge resources are efficiently absorbed and utilised. Policy stability, transparent administration, and predictable funding mechanisms are particularly important. Governments should establish central Innovation Delivery Units to coordinate fragmented R&D policies, introduce performance benchmarks for judicial efficiency, especially in IP and commercial disputes—and concentrate investments into regional smart innovation zones where R&D subsidies, digital infrastructure, and technology-transfer services are geographically clustered. These reforms directly strengthen institutional quality, reduce friction in innovation processes, and improve the overall absorptive capacity of national innovation systems.

These priorities align with the European Innovation Scoreboard (European Commission, 2023), which also highlights regional innovation inequalities and the need for cohesive, multi-level governance approaches to improve knowledge utilisation efficiency.

The DEA results support theoretical perspectives that conceptualise innovation efficiency as a function of system integration rather than resource abundance. As proposed by Lundvall (2016) and Edvinsson & Malone (1997), the capacity to utilise intellectual capital effectively depends on the interaction between human, structural, and relational elements within a coherent institutional framework. The north–south and west–east efficiency divide thus reflects systemic maturity differences, not merely input disparities.

Conclusion

This comprehensive study provides an in-depth, scholarly analysis of the evolution of the National Intellectual Capital (NIC) efficiency within the European Union over the past two decades. Utilizing Data Envelopment Analysis (DEA), the findings initially reveal marked disparities in efficiency levels, delineating a clear distinction between the older, industrialized member states and their newer counterparts. Over time, these disparities have progressively diminished, underscoring the effectiveness of EU-led policy harmonization, increased investments in research and development (R&D), and improvements in educational infrastructures, all aligned with the EU's overarching innovation strategies.

Spatially, the analysis demonstrates that Northern and Western European nations, such as those in Scandinavia and the Benelux region, consistently register high DEA efficiency scores. These results are indicative of their well-developed innovation ecosystems, robust institutional frameworks, and adept resource management practices. Conversely, Southern and Eastern European countries tend to record lower efficiency scores, which reflect structural challenges including less developed research infrastructures, weaker innovation systems, and comparatively lower R&D expenditures. Nevertheless, emerging evidence of progress in some of these nations suggests a potential trajectory towards long-term convergence within the EU.

Regarding the three dimensions of NIC, Structural Capital emerges as the most stable component, exerting the greatest influence on overall efficiency, while Human Capital exhibits greater variability and responsiveness to policy reforms. Relational Capital functions as a stabilizing factor, fostering open trade and collaborative networks that underpin system resilience.

By the year 2022, a majority of EU member states demonstrate moderate to high levels of DEA efficiency, indicative of a more integrated and balanced innovation landscape. Despite these advancements, persistent regional disparities highlight the imperative for targeted policy interventions aimed at bolstering human capital, enhancing research infrastructure, and strengthening institutional capacities. Such measures are essential to ensuring equitable participation across all member states in the knowledge-based economy, thereby supporting sustained, innovation-driven economic growth throughout the European Union.

Importantly, this study also incorporates a robust second-stage analytical framework to deepen the empirical insights generated by the DEA models. The use of Tobit regression, fractional response models (FRM), and OLS estimations provides strong evidence on the institutional, socioeconomic, and structural factors driving variations in NIC efficiency. Furthermore, the application of both Variable Returns to Scale (VRS) and Constant Returns to Scale (CRS) DEA specifications confirms the consistency and reliability of the efficiency patterns observed. Complementary assessments of sigma and beta convergence shed additional light on whether EU member states are becoming more similar in their NIC efficiency over time or whether divergence remains entrenched. Together, these methodological extensions strengthen the study's conclusions and offer a multidimensional perspective on the evolution of intellectual capital across the EU, reinforcing the need for coherent, long-term policy strategies to support sustainable convergence.

Credit Authorship Contribution Statement

Slyvkanych, N. was responsible for the conceptualization, methodology, data curation, and formal analysis of the study. The author conducted the investigation, prepared the original draft, and revised the manuscript, and approves the final version of the paper.

Acknowledgments/Funding

N/A

Conflict of Interest Statement

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

Data Availability Statement: The data that support the findings of this study were obtained from World Bank, UNESCO and WIPO and are available at https://data.worldbank.org/, https://databrowser.uis.unesco.org/, and https://www.wipo.int/en/web/global-brand-database

References

Afsharian, M., Kamali, S., Ahn, H., & Bogetoft, P. (2024). Individualized second stage corrections in data envelopment analysis. *European Journal of Operational Research,* 317(2), 563–577. https://doi.org/10.1016/j.ejor.2024.04.008

Amundsveen, R., Kordahl, O. P., Kvile, H. M., & Langset, T. (2014). Second stage adjustment for firm heterogeneity in DEA: A novel approach used in regulation of Norwegian electricity DSOs. Recent Developments in Data Envelopment Analysis and Its Applications, 12, 334 – 341. http://deazone.com/proceedings/DEA2014-Proceedings.pdf

Archibugi, D., & Filippetti, A. (2018). The retreat of public research and its adverse consequences on innovation. Technological Forecasting and Social Change, 127, 97–111. https://doi.org/10.1016/j.techfore.2017.05.022

Balcerzak, A. P. (2016). Multiple-criteria Evaluation of Quality of Human Capital in the European Union Countries. Economics & Sociology, 9(2), 11–26. https://doi.org/10.14254/2071-789X.2016/9-2/1

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, 30(9), 1078–1092.

Banker, R., Natarajan, R., & Zhang, D. (2019). Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using Data Envelopment Analysis: Second stage OLS versus bootstrap approaches. European Journal of Operational Research, 278(2), 368–384. https://doi.org/10.1016/j.ejor.2018.10.050

Bontis, N. (2002). Managing Organizational Knowledge by Diagnosing Intellectual Capital: Framing and Advancing the State of the Field. World Congress on Intellectual Capital Readings, 13–56. https://doi.org/doi:10.1016/B978-0-7506-7475-1.50006-3

Bradley, K. (1997). Intellectual Capital and the New Wealth of Nations II. Business Strategy Review, 8(4), Article 4. https://doi.org/10.1111/1467-8616.00046

Brooking, A. (1997). Intellectual Capital: Core asset for the third millennium (p. 224). Cengage Learning.

Cabrilo, S., Dahms, S., & Tsai, F.-S. (2024). Synergy between multidimensional intellectual capital and digital knowledge management: Uncovering innovation performance complexities. Journal of Innovation & Knowledge, 9(4), 100568. https://doi.org/10.1016/j.jik.2024.100568

Carayannis, E., & Grigoroudis, E. (2014). Linking innovation, productivity, and competitiveness: Implications for policy and practice. The Journal of Technology Transfer, 39(2), 199–218. https://doi.org/10.1007/s10961-012-9295-2

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European Journal of Operational Research, 2(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chowdhury, F., Audretsch, D. B., & Belitski, M. (2019). Institutions and Entrepreneurship Quality. Entrepreneurship Theory and Practice, 43(1), 51–81. https://doi.org/10.1177/1042258718780431

Coelli, T. J., Prasada Rao, D. S., O'Donnell, C. J., & Battese, G. E. (Eds). (2005). Index Numbers and Productivity Measurement. In An Introduction to Efficiency and Productivity Analysis (pp. 85–132). Springer, Bostonm MA. https://doi.org/10.1007/0-387-25895-7_4

Cooper, W., Seiford, L., & Tone, K. (2007). Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software. https://doi.org/10.1007/978-0-387-45283-8

Corrado, C., Haltiwanger, J., & Sichel, D. (2005). Measuring Capital in the New Economy. University of Chicago Press. https://doi.org/10.7208/chicago/9780226116174.001.0001

Crescenzi, R., Iammarino, S., Ioramashvili, C., Rodríguez-Pose, A., & Storper, M. (2020). The Geography of Innovation and Development: Global Spread and Local Hotspots. Department of Geography and Environment. https://eprints.lse.ac.uk/105116/1/Crescenzi_geography_of_innovation_and_development_ published.pdf

Drucker, P. F. (1954). The Practice of Management (1st Edition, p. 416). Harper & Roe.

Drucker, P. F. (1985). Innovation and Entrepreneurship. Harper & Row.

Dumay, J., & Gagarina, T. (2012). Investigating IC research: A critical examination. 164–171.

Edquist, C. (2013). Systems of Innovation: Technologies, Institutions and Organizations. Taylor and Francis.

Edvinsson, L., & Malone, M. S. (1997). Intellectual Capital: Realizing Your Company's True Value by Finding Its Hidden Brainpower (p. 240). Harper Business.

Edvinsson, L., & Stenfelt, C. (1999). Intellectual Capital of Nations - For Future Wealth Creation. *Journal of Human Resource Costing & Accounting*, 4(1), Article 1. https://doi.org/10.1108/eb029051

European Commission. (2023). European innovation scoreboard 2023 - Research and innovation. European Innovation Scoreboard 2023. https://research-and-innovation.ec.europa.eu/knowledge-publications-tools-and-data/publications/all-publications/european-innovation-scoreboard-2023_en

Fagerberg, J., & Srholec, M. (2008). National innovation systems, capabilities and economic development. Research Policy, 37(9), 1417–1435. https://doi.org/10.1016/j.respol.2008.06.003

Gianelle, C., Guzzo, F., Barbero, J., & Salotti, S. (2024). The governance of regional innovation policy and its economic implications. The Annals of Regional Science, 72(4), 1231–1254. https://doi.org/10.1007/s00168-023-01241-2

Guthrie, J., Ricceri, F., & Dumay, J. (2012). Reflections and projections: A decade of Intellectual Capital Accounting Research. The British Accounting Review, 44(2), Article 2. https://doi.org/10.1016/j.bar.2012.03.004

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. European Journal of Operational Research, 181(1), 425–435. https://doi.org/10.1016/j.ejor.2006.05.019

Huian, M. C., Bisogno, M., & Mironiuc, M. (2025). Managing Intellectual Capital Components in Technology Transfer Processes: The Case of Romanian Public Research Institutes. Journal of the Knowledge Economy, 16(3), 12664–12697. https://doi.org/10.1007/s13132-024-02418-6

Jednak, S., Dmitrović, V., & Damnjanović, V. (2017). Intellectual Capital as a Driver of Economic Development. Economic Review: Journal of Economics and Business, 15(2), 77–84.

Kozuń-Cieślak, G. B., & Murray Svidroňová, M. (2024). Assessing Innovation Efficiency: The Case of Post-Communist EU Member States. Ekonomista, 1–22. https://doi.org/10.52335/ekon/194189

Krammer, S. M. S. (2017). Science, technology, and innovation for economic competitiveness: The role of smart specialization in less-developed countries. Technological Forecasting and Social Change, 123, 95–107. https://doi.org/10.1016/j.techfore.2017.06.028

Labra, R., & Paloma Sánchez, M. (2013). National intellectual capital assessment models: A literature review. Journal of Intellectual Capital, 14(4), Article 4. https://doi.org/10.1108/JIC-11-2012-0100

Lev, B. (2018). The deteriorating usefulness of financial report information and how to reverse it. Accounting and Business Research, 48, 465–493. https://doi.org/10.1080/00014788.2018.1470138

Lin, C. Y.-Y., & Edvinsson, L. (2011). National Intellectual Capital: A Comparison of 40 Countries. Springer New York. https://doi.org/10.1007/978-1-4419-7377-1

Lundvall, B.-Å. (2016). The Learning Economy and the Economics of Hope. Anthem Press. https://doi.org/10.26530/OAPEN_626406

Manzari, M., Kazemi, M., Nazemi, S., & Pooya, A. (2012). Intellectual capital: Concepts, components and indicators: A literature review. Management Science Letters, 2(7), 2255–2270. https://doi.org/10.5267/j.msl.2012.07.018

Marinelli, L., Bartoloni, S., Pascucci, F., Gregori, G. L., & Farina Briamonte, M. (2022). Genesis of an innovation-based entrepreneurial ecosystem: Exploring the role of intellectual capital. Journal of Intellectual Capital, 24(1), 10-34. https://doi.org/10.1108/JIC-09-2021-0264

Martín-Gamboa, M., & Iribarren, D. (2021). Chapter 16—Coupled life cycle thinking and data envelopment analysis for quantitative sustainability improvement. In J. Ren (Ed.), Methods in Sustainability Science (pp. 295–320). Elsevier. https://doi.org/10.1016/B978-0-12-823987-2.00003-9

Nahapiet, J., & Ghoshal, S. (1998). Social Capital, Intellectual Capital, and the Organizational Advantage. The Academy of Management Review, 23(2), 242–266. https://doi.org/10.2307/259373

Nitkiewicz, T., Pachura, P., & Reid, N. (2014). An appraisal of regional intellectual capital performance using Data Envelopment Analysis. Applied Geography, 53, 246–257. https://doi.org/10.1016/j.apgeog.2014.06.011

OECD. (2021). OECD Science, Technology and Innovation Outlook 2020: Science and Innovation in Times of Crisis. OECD Publishing. https://doi.org/10.1787/75f79015-en

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. Journal of Applied Econometrics, 11(6), 619–632. https://doi.org/10.1002/(SICI)1099-1255(199611)11:6%253C619::AID-JAE418%253E3.0.CO;2-1

Pedro, E., Leitão, J., & Alves, H. (2018). Back to the future of intellectual capital research: A systematic literature review. Management Decision, 56(11), Article 11. https://doi.org/10.1108/MD-08-2017-0807

Radosevic, S., & Yoruk, E. (2016). Why do we need a theory and metrics of technology upgrading? Asian Journal of Technology Innovation, 24. https://doi.org/10.1080/19761597.2016.1207415

Ramalho, E. A., Ramalho, J. J. S., & Henriques, P. D. (2010). Fractional regression models for second stage DEA efficiency analyses. Journal of Productivity Analysis, 34(3), 239–255. https://doi.org/10.1007/s11123-010-0184-0

Ren, J. (2008). Measure Research in Regional Intellectual Capital on the Basis of Multifactor Level Fuzzy Evaluation Method. 2008 Fifth International Conference on Fuzzy Systems and Knowledge Discovery, 589–593. https://doi.org/10.1109/FSKD.2008.591

Rodríguez-Pose, A., & Di Cataldo, M. (2015). Quality of government and innovative performance in the regions of Europe. Journal of Economic Geography, 15(4), 673–706. https://doi.org/10.1093/jeg/lbu023

Roos, G., & O'Connor, A. (2015). Government policy implications of intellectual capital: An Australian manufacturing case study. Journal of Intellectual Capital, 16(2), Article 2. https://doi.org/10.1108/JIC-02-2015-0016

Roos, G., & Roos, J. (1997). Measuring your company's intellectual performance. Long Range Planning, 30(3), Article 3. https://doi.org/10.1016/S0024-6301(97)90260-0

Schiuma, G., & Lerro, A. (2008). Knowledge-based capital in building regional innovation capacity (No. 5). 12(5), Article 5. https://doi.org/10.1108/13673270810902984

Schumpeter, J. A. (1983). The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle. Transaction Books. ISBN: 0878556982, 978-0878556984

Simar, L., & Wilson, P. W. (2011). Two-stage DEA: Caveat emptor. Journal of Productivity Analysis, 36(2), 205–218. https://doi.org/10.1007/s11123-011-0230-6

Sklavos, G., Zournatzidou, G., Ragazou, K., & Sariannidis, N. (2025). Green accounting and ESG-driven eco-efficiency in European financial institutions: A two-stage DEA–CRITIC-TOPSIS evaluation. PLOS One, 20(10), e0334882. https://doi.org/10.1371/journal.pone.0334882

Stewart, T. A., & Losee, S. (1994). Your Company's Most Valuable Asset: Intellectual Capital (No. 130). 130, Article 130.

Tobin, J. (1958). Estimation of Relationships for Limited Dependent Variables. Econometrica, 26(1), 24–36. https://doi.org/10.2307/1907382

Yadava, A. K., Chakraborty, S., & Gupta, S. (2025). Benchmarking the performance of Indian electricity distribution companies: The applications of multi-stage robust DEA and SFA models. Energy Economics, 145, 108396. https://doi.org/10.1016/j.eneco.2025.108396

Youndt, M. A., Subramaniam, M., & Snell, S. A. (2004). Intellectual Capital Profiles: An Examination of Investments and Returns*: Intellectual Capital Profiles. Journal of Management Studies, 41(2), Article 2. https://doi.org/10.1111/j.1467-6486.2004.00435.x

Zhang, X., Wei, F., Xia, Q., Song, S., & Wang, D. (2024). Efficiency assessment of two-stage systems with fixed-sum outputs: A noncooperative DEA model with uncertain stage priority. Expert Systems with Applications, 253, 124274. https://doi.org/10.1016/j.eswa.2024.124274