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Importance of Sustainable Development Goal 3 & 4 in Relation to Overall Sustainable Development

Znaczenie 3 i 4 Celów Zrównoważonego Rozwoju w kontekście ogólnego zrównoważonego rozwoju

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Abstract
This study investigated the importance of Sustainable Development Goals 3 and 4 for overall sustainable development. Hierarchical cluster analysis was applied to the healthcare systems of 31 European countries, including all EU member states as well as the United Kingdom, Norway, Iceland, and Switzerland. The analysis covers the years 2014 and 2019–2022 and is based on indicators of population health status (life expectancy, healthy life years, perceived health), tertiary educational attainment, preventable and treatable mortality, and healthcare expenditure.
The results reveal a consistent division into two main clusters. Cluster 1 is composed primarily of Western and Northern European countries, along with high-performing non-EU states such as Switzerland, and is characterized by stronger health outcomes, higher education levels, and greater healthcare expenditure. Cluster 2 consists largely of Central and Eastern European member states, which systematically report weaker results across most indicators. In addition, smaller clusters (Clusters 3 and 4) emerge in specific years, grouping countries with distinctive profiles. These include high-performing countries such as Ireland, Luxembourg, and Cyprus, as well as countries with relatively high educational attainment but lower health outcomes, such as Latvia and Lithuania.
Comparison with established healthcare system classifications confirms the relevance of these patterns. The best-performing clusters overlap with advanced Bismarck and Beveridge systems, the high-capacity groups identified by Reibling et al. (2019), and the higher-expenditure groups of Di Gioacchino et al. (2024). Conversely, weaker clusters, particularly those in Central and Eastern Europe, align with Bismarck or mixed models, Etatist Social Health Insurance systems, or low-supply systems, and are typically associated with lower healthcare expenditure. Overall, the findings highlight persistent regional divides in healthcare performance.

Key words: healthcare systems, cluster analysis, health expenditure, sustainable development

Streszczenie
W niniejszym badaniu zbadano znaczenie Celów Zrównoważonego Rozwoju 3 i 4 dla ogólnego zrównoważonego rozwoju. Hierarchiczną analizę skupień zastosowano do systemów opieki zdrowotnej 31 krajów europejskich, w tym wszystkich państw członkowskich UE, a także Wielkiej Brytanii, Norwegii, Islandii i Szwajcarii. Analiza obejmuje lata 2014 oraz 2019–2022 i opiera się na wskaźnikach stanu zdrowia populacji (oczekiwana długość

życia, lata zdrowego życia, postrzegany stan zdrowia), poziomie wykształcenia wyższego, śmiertelności, której można zapobiec i którą można leczyć, oraz wydatkach na opiekę zdrowotną.
Wyniki wskazują na spójny podział na dwa główne klastry. Klaster 1 składa się głównie z krajów Europy Zachodniej i Północnej, a także z krajów spoza UE o wysokiej wydajności, takich jak Szwajcaria, i charakteryzuje się lepszymi wynikami zdrowotnymi, wyższym poziomem wykształcenia i większymi wydatkami na opiekę zdrowotną. Klaster 2 składa się głównie z państw członkowskich Europy Środkowej i Wschodniej, które systematycznie wykazują słabsze wyniki w większości wskaźników. Ponadto, w określonych latach pojawiają się mniejsze klastry (Klastry 3 i 4), grupujące kraje o charakterystycznych profilach. Należą do nich kraje o wysokich wynikach, takie jak Irlandia, Luksemburg i Cypr, a także kraje o stosunkowo wysokim poziomie wykształcenia, ale gorszych wynikach zdrowotnych, takie jak Łotwa i Litwa.
Porównanie z ugruntowanymi klasyfikacjami systemów opieki zdrowotnej potwierdza trafność tych wzorców. Klastry o najlepszych wynikach pokrywają się z zaawansowanymi systemami Bismarcka i Beveridge'a, grupami o wysokiej przepustowości zidentyfikowanymi przez Reiblinga i in. (2019) oraz grupami o wyższych wydatkach zidentyfikowanymi przez Di Gioacchino i in. (2024). Z kolei słabsze klastry, szczególnie te w Europie Środkowo-Wschodniej, odpowiadają modelom Bismarcka lub mieszanym, państwowym systemom ubezpieczeń zdrowotnych lub systemom o niskiej podaży i zazwyczaj wiążą się z niższymi wydatkami na opiekę zdrowotną.
Ogólnie rzecz biorąc, wyniki badań podkreślają utrzymujące się regionalne różnice w wynikach opieki zdrowotnej.

Słowa kluczowe: systemy opieki zdrowotnej, analiza klastrów, wydatki na opiekę zdrowotną, zrównoważony rozwój

1. Introduction

Health is a fundamental component of wellbeing, quality of life, and sustainable development. The motivation of this study is to better understand the factors that determine health status at the country level and to explore the relationships between healthcare system models and sustainable development (SD). The analysis focuses on the EU Sustainable Development Goal (SDG) indicator set, in particular SDG 3 (*Good health and well-being*) and SDG 4 (*Quality education*), and their role in shaping the overall SD path (Eurostat, 2025). Comparing the pre-COVID, COVID, and post-COVID phases is essential to fully understand the pandemic's impact during the analysed period.
The aim of the study is to identify similarities and differences in healthcare systems across a sample of 32 countries and to evaluate the findings in relation to existing classifications of healthcare systems. The sample included the EU countries, the United Kingdom (UK), and three non-EU European countries: Norway, Iceland, and Switzerland. We also examine whether the observed patterns correspond to broader regional divides, such as Northern vs. Western vs. Southern Europe, older vs. newer EU member states (with the latter referring to countries that joined since 2004, predominantly in Central and Eastern Europe), and EU vs. non-EU countries.
We hypothesize that countries with higher healthcare expenditure and greater tertiary education attainment achieve better health outcomes, positioning them closer to the overall SD path.
Small countries – whether older EU members (e.g., Luxembourg), newer EU members (e.g., Malta, Cyprus), or non-EU states (e.g., Iceland) – are also considered. These cases are important as they often face specific conditions that distinguish them from larger states.

2. Literature review

A substantial body of research has examined the relationship between health, sustainable development (SD), wellbeing, and quality of life at the national level. Santana et al. (2020) advanced both theory and practice in population health by proposing a model that integrates health outcomes with multisectoral determinants. They developed EU-specific tools with potential broader applicability. Using the Population Health Index, their study highlighted regional disparities, investment priorities, and outlined three possible scenarios for 2030: Failing Europe (widening inequalities), Sustainable Prosperity (reduced inequalities), and Being Stuck (status quo).
Clustering methods have become increasingly important in comparative health system research, offering new perspectives beyond traditional typologies such as the Bismarck and Beveridge models. These approaches provide an additional perspective on the heterogeneity of healthcare systems alongside traditional typologies such as the Bismarck and Beveridge models.
The earliest systematic typologies date back to Field (1973), who classified healthcare systems along the dimensions of ownership and doctors' autonomy. He identified four system types: the pluralist system, characterized by high private provision and high medical autonomy; the health insurance system, where social insurance actors play a strong role while medical autonomy remains high; the health service system, with mostly state-owned facilities

and high medical autonomy; and the socialized health system, in which all facilities are owned and controlled by the state.

Building on this, Schieber (1987) introduced three additional models based on coverage, funding, and ownership: the National Health Service model, which combines universal coverage with tax financing and public provision; the Social Insurance model, which offers universal coverage with social insurance financing and mixed ownership; and the Private Insurance model, which relies entirely on private insurance coverage, financing, and provision.

Two main approaches have emerged: one focuses on health policy actors, the other on institutional settings of healthcare systems. Later studies refined these typologies. Rothgang et al. (2010) combined governance, financing, and provision with three actor types (public, private, and private non-profit), resulting in 27 possible combinations. Among these, three ideal types were identified: State, Societal, and Private healthcare systems. (Rothgang et al., 2010; Wendt et al. (2009). Building on this framework, Böhm et al. (2013) empirically tested which of these types exist in the OECD and identified five system types, partly overlapping with the classical Beveridge–Bismarck–Mixed classification. The National Health Service (NHS) type, tax-financed and closest to the Beveridge model, includes Denmark, Finland, Iceland, Norway, Sweden, Portugal, Spain, and the United Kingdom. The National Health Insurance (NHI) type, based on a single public insurer and predominantly private provision, covers Australia, Canada, Ireland, Italy, and New Zealand. The Social Health Insurance (SHI) type, corresponding most closely to the Bismarck model, is represented by Austria, Germany, Luxembourg, and Switzerland. The largest group, the Etatist Social Health Insurance (Etatist SHI), combining state regulation with societal financing and private provision, includes Belgium, Estonia, France, the Czech Republic, Hungary, the Netherlands, Poland, Slovakia, Israel, Japan, and South Korea. Finally, the Private Health System type is represented by the United States, while Slovenia is described as a mixed case with societal financing but predominantly state provision.

A second line of research has focused on institutional settings rather than actors, exploring how financing, provision, and regulation interact to produce system-level outcomes. Reibling (2010) and Wendt (2009, 2014) extended earlier studies by including dimensions such as access regulation, physician remuneration, and distinctions between inpatient and outpatient care.

Wendt et al. (2009) classified healthcare systems in 15 European countries using expenditure, financing, provision, and access indicators. Cluster analysis identified three types: systems oriented toward health service provision, characterized by many providers and free access to doctors; systems with universal but controlled access, where equal access is prioritized over free choice; and low-budget, restricted-access systems, marked by limited resources, high out-of-pocket payments, and mandatory registration with a general practitioner.

Reibling et al. (2019) extended OECD healthcare typologies by combining institutional classifications with health policy research. Using five dimensions (supply, public–private mix, access regulation, primary care orientation, and performance), they applied cluster analysis to 29 OECD countries and distinguished five system types. The supply- and choice-oriented public type includes AU, AT, BE, CZ, DE, FR, IE, IS, LU, SL. The performance- and primary-care-oriented public type covers FI, JA, KO, NO, NZ, PT, SE. The regulation-oriented public type consists of CA, DK, ES, IT, NL, UK. The low-supply and low-performance mixed type groups EE, HU, PL, SK. Finally, the supply- and performance-oriented private type is represented by CH and US.

Di Gioacchino, Ghignoni, and Sabani (2024) cluster 25 European healthcare systems along three axes: total health expenditure, the public–private funding mix with explicit attention to duplicate voluntary health insurance, and the balance between primary and secondary care. They identified five types: high-spending, secondary-care-oriented systems (BE, FR, IS, DE, CH, AT, CZ); high-spending, primary-care-oriented systems (SE, DK, FI, NL, NO, UK); medium-spending, primary-care-oriented systems (ES, IT, EE, SI, PT); and low-spending, secondary-care-oriented systems (LT, PL, HU, SK, LV, GR), where out-of-pocket payments are relatively high. Ireland (IE) emerged as a distinct outlier with very high per-capita expenditure, a primary-care orientation, heavy reliance on duplicate voluntary health insurance, and only about 73% of spending financed through general taxation. Their results show that higher healthcare expenditure – particularly public spending – is associated with better health outcomes and lower socio-economic disparities, while stronger primary-care orientation is not linked to improved outcomes or reduced inequalities; moreover, the supposed decongestion effect of voluntary health insurance is questioned.

Recent studies have applied cluster analysis to health outcomes and system performance. Top and Cinaroglu (2021) classified European countries by life expectancy (LE) at birth using hierarchical clustering on time series data (1980–2015). They further applied Random Forest and CART methods to identify economic growth and financial development as key predictors of long-term LE. Their results show a clear East–West divide, with Eastern and Western countries largely forming separate clusters.

Similarly, Nurmeksela et al. (2023) used k-means clustering to analyse patient satisfaction in Finnish acute care hospitals, finding generally high levels of satisfaction. DeLong et al. (2025) applied clustering to UK Biobank data to group physical morbidities among adults aged 37–73.

Beyond health systems, broader social determinants also shape outcomes. Raghupathi and Raghupathi (2020) confirmed this for 26 OECD countries (1995–2015), showing that tertiary education strongly influences infant mortality, life expectancy, vaccination, and enrolment, with higher education linked to better health and longer life. Expanding education thus improves population health and reduces inequalities.

Finally, methodological foundations were laid by Everitt et al. (2011), while Murtagh and Contreras (2017) reviewed hierarchical clustering algorithms, including Ward's method, which remains common in health policy research.

Hierarchical Cluster Analysis (HCA) has already been applied in the author's previous work, and this study builds directly on that line of research. Drastichová (2017) assessed the sustainability of EU countries together with Norway and Switzerland in terms of well-being across three dimensions of sustainable development (SD) and aspects of decoupling. In a follow-up, Drastichová (2018) used HCA with five composite indices covering the three dimensions of SD to group the EU countries, Norway, Switzerland, Iceland, the USA, and Canada into three clusters in 2016. Drastichová and Filzmoser (2019) extended the analysis by applying both HCA and Principal Component Analysis (PCA) to 12 SDG indicators for the 28 EU countries and Norway in the period 2012–2016. Four clusters were identified each year, with results showing consistent differences in sustainability performance: the most developed EU countries formed the best-performing cluster, while the least developed countries formed the weakest. Transitional economies ranked second-best, and Southern countries were placed in the second-worst cluster. Shifts in cluster membership also revealed progress over time, such as Ireland moving to the best-performing group in 2013, and Slovakia and Hungary advancing from the weakest to a higher-performing cluster. Together, these studies demonstrated the usefulness of clustering methods for tracking sustainability performance and highlighted the heterogeneity of progress across Europe.

Together, this body of literature offers classifications of healthcare systems based on features crucial for their efficiency and sustainability. Some studies explore the relationship between educational level and health status, while others justify the use of clustering methods to examine healthcare system efficiency, resilience, and sustainability. Through methodological rigor and cross-national data, these approaches provide valuable insights into whether system typologies such as the basic Beveridge versus Bismarck distinction, other classifications, or geographic groupings like Northern, Southern, and Eastern Europe correspond to measurable patterns in healthcare indicators.

3. Data and methodology

This section presents the data and methodology used in the analysis.

3.1. Data

To examine cross-country similarities and differences in health outcomes, health expenditures, education, and mortality patterns, we applied hierarchical cluster analysis separately for each available year in the dataset. The sample included 32 European countries, comprising all EU member states, the United Kingdom, Norway, Iceland, and Switzerland.

Table 1. Indicators included in the cluster analysis, source: (Eurostat, 2025; European Commission, Eurostat, 2025)

Tertiary educational attainment (TEA): the share of the population aged 25-34 who have successfully completed tertiary studies (e.g. university, higher technical institution, etc.); *Percentage*
Life expectancy (LE) at a given age: the average number of years a person is expected to live after reaching that age, assuming current age-specific mortality rates remain constant for the rest of their life; The age group of less than one year LE14; *Year*
Healthy life years at birth (HALE): the number of years that a person at birth is still expected to live in a healthy condition; Combines information on mortality and morbidity; A healthy condition – defined by the absence of limitations in functioning/disability; *Year*
Standardised preventable and treatable mortality (SPTM) – Avoidable mortality includes deaths that could be prevented through effective public health and primary prevention (preventable) or reduced through timely and effective healthcare (treatable). The causes cover selected infectious diseases, cancers, circulatory and respiratory diseases, metabolic disorders, complications of pregnancy and childbirth, congenital conditions, injuries, and alcohol- and drug-related disorders. Data are expressed as standardised death rates, adjusted to the European standard population, which ensures comparability across countries and over time; *Rate*
Total health care expenditure (HCE): quantifies the economic resources dedicated to health functions, excluding capital investment. Concerns primarily healthcare goods and services consumed by residents, irrespective of where that consumption takes place or who is paying for it; *Percentage of gross domestic product (GDP)*
Share of people with good or very good perceived health (PHG) – a subjective measure on how people judge their health in general on a scale from *very good* to *very bad*. It is expressed as the share of the population aged 16 or over perceiving itself to be in *good* or *very good* health. The data stem from the EU Statistics on Income and Living Conditions (EU SILC). Indicators of perceived general health have been found to be a good predictor of people's future health care use and mortality; *Percentage*

Note: after the definition of the indicator, a unit of measure is indicated.

Data from Eurostat (2025) were used for 2014 and for the period 2019–2022. The set of indicators included perceived health status (PHG), total healthcare expenditure as a share of GDP (HCE), tertiary educational attainment (TEA), standardized preventable and treatable mortality (SPTM), life expectancy (LE), and healthy life expectancy (HALE). These indicators capture multiple dimensions of population health and health system performance and are described in Table 1.

As regards the relationships of the indicators with SD the following aspects are necessary. Variables. Both LE and HALE are health status indicators with LE reflecting the quantity of life and HALE reflecting both the quantity and quality of life. PHG is a measure of subjective well-being (referred to as health status indicators – objective (LE, HALE), subjective (PHG)). All these indicators reflect SDG 3, aims to ensure health and well-being for all, in the the EU SDG indicator set. Indicators of avoidable mortality (SPTM) offer a general starting point to evaluate the effectiveness of public health and healthcare systems in reducing deaths from various diseases and injuries (see more on OECD, 2023). TEA is a socioeconomic determinant of SD included in SDG 4, which seeks to ensure access for all to quality education. HCE (% GDP) captures health care system resourcing.

3.2. Methodology

As the main method, hierarchical clustering (HC) was applied. HC begins by treating each observation as a separate cluster and then consecutively merges the most similar clusters until all observations belong to a single cluster. The procedure was based on a squared Euclidean distance matrix, applying Ward's minimum variance method. This approach minimizes within-cluster variance and is widely used in health system research due to its robustness and interpretability (Ward, 1963; Murtagh & Legendre, 2014; Murtagh & Contreras, 2017; Everitt et al., 2011). The number of clusters was fixed to four (k=4) to ensure comparability across years and to provide an interpretable solution that balances parsimony with differentiation. Squared Euclidean distance was chosen as the dissimilarity measure, as it is the most widely applied metric for continuous variables and can also be robustly used with mixed-scale data (Reibling et al., 2019).

3.2.1. Data preprocessing

For each year (2014, 2019–2022) we constructed a country-by-indicator matrix by selecting variables with the matching two-digit suffix (e.g., *TEA19*, *LE19*). Countries with more than half of the six indicators missing in that year (≥4) were excluded; this occurred only for the UK in 2019–2022 (the UK is retained in 2014). The remaining missingness was minimal – eight cells in total across the whole panel: Italy (1), Norway (1), and Iceland (6; at most two in any single year). These entries were imputed by the within-year median of the respective indicator. After imputation, all country-year rows used for clustering were complete. To render indicators comparable across units, each year's matrix was standardized to z-scores.

3.2.2. Clustering

We applied agglomerative hierarchical clustering using Ward's minimum-variance criterion (R: hclust, method = *ward.D2*). Dissimilarities were computed as Euclidean distances on the year-specific z-scores. With ward.D2, using Euclidean distances is equivalent to optimizing the increase in total within-cluster sum of squares (Ward's original criterion). We fixed the number of clusters at $k = 4$ across years for comparability and interpretability. (As a robustness option, our code can also select k via the silhouette; results are reported for the fixed-k solution.)

To meaningfully interpret the identified clusters, we compared them with established health system typologies. In particular, we assessed their alignment with the Bismarck and Beveridge models, as well as typology-based frameworks proposed by Böhm et al. (2013) and Reibling et al. (2019), to ensure that the statistical findings are grounded in a substantive understanding of institutional and regional healthcare contexts.

4. Results of the analysis

First, the results of the HCA are described and interpreted (4.1). Subsequently, the results are put into the context with three existing health care system classifications.

4.1. Results of the Hierarchical Cluster Analysis

The dendrograms (Figure 1), descriptive statistics (Table 1), and cluster maps are provided in the Annex (Maps 1–4). Table 2 shows the composition of the clusters across the monitored years. The dendrograms clearly indicate that two main clusters emerge at a higher level of distance. The division into Cluster 1 and Cluster 2 broadly corresponds to the distinction between Western and Northern European countries – including non-EU members such as Norway, Iceland, Switzerland, and the United Kingdom – and the newer Central and Eastern European member states.

Accordingly, most Northern countries are consistently grouped in Cluster 1, while the post-2004 accession countries are largely found in Cluster 2. Clusters 3 and 4 appear more unstable and context-specific; their composition varies significantly across years, often including Baltic states, some Southern European, and occasionally Northern or Central/Eastern European countries. In essence, the basic classification can be reduced to two main groups: the more advanced countries in Cluster 1 and the less advanced ones in Cluster 2, while Clusters 3 and 4 capture countries with mixed profiles or specific outlying features relative to the indicators.

Table 2. The results of Hierarchical Clustering – 4 clusters in 2014-2020, source: author's elaboration using R statistical software

Year	Cluster 1	Cluster 2	Cluster 3	Cluster 4
2014	BE, DK, DE, FR, IT, NL, AT, PT, SI, FI, CH, UK	BG, CZ, HR, HU, RO, SK	EE, LV, LT, PL	IE, GR, ES, CY, LU, MT, SE, IS, NO
2019	BE, DK, FR, NL, AT, PT, GR, IS, SI, FI, CH	BG, CZ, HR, EE, LV, LT, HU, PL, RO, SK	DE, ES, IT, MT, NO, SE	CY, LU, IE,
2020	BE, DK, DE, ES, FR, IT, MT, NL, AT, GR, SI, FI, SE, IS, NO, CH	BG, HU, RO	CZ, HR, EE, LT, LV, PL, PT, SK	CY, IE, LU
2021	BE, DK, DE, ES, IT, MT, NL, AT, SI, GR, PT, FI, SE, IS, NO, CY, FR, CH	BG, CZ, HR, HU, EE, PL, RO, SK	IE, LU	LV, LT
2022	BE, DK, DE, ES, FR, NL, AT, SI, PT, FI, SE, IS, CH	BG, CZ, HR, HU, EE, PL, RO, SK	IE, IT, MT, LU, NO, GR, CY	LV, LT

Turning to the average values of the clusters, several patterns are visible. HALE reached its highest average in Cluster 3 in 2019. HCE is highest in Cluster 1 in almost all years, except in 2019 when Cluster 3 (including DE, SE, and NO) slightly surpassed it. Cluster 1 countries are generally stable across the years and include Western and Northern developed states, characterized by high HCE relative to GDP. LE remains consistently high in Cluster 1 and is often among the highest together with Clusters 3 and 4, depending on composition. PHG values are also elevated in Cluster 1, peaking in Cluster 4 during the first three years and later in Cluster 3 after compositional shifts. In 2020–2021, Cluster 4 recorded the lowest PHG values because it consisted only of two Baltic countries. TEA is high in Cluster 1, though relatively lower in 2014 due to low values in Italy and Germany. Cluster 4 shows the highest TEA in every year, even when reduced to Latvia and Lithuania in 2021–2022. Lithuania, in particular, stands out with some of the highest TEA values in the entire sample, a crucial aspect for its sustainable development trajectory. SPTM is highest in less advanced EU countries (Cluster 2), but also elevated in Cluster 3 in 2014 and 2020, and extremely high in Cluster 4 during 2021–2022.

Cluster 2 consistently represents the lowest-performing group: low values of HALE, LE, PHG, HCE, and TEA, combined with high preventable and treatable mortality. The opposite is observed in Cluster 1, although some outliers affect averages. For instance, several Cluster 1 countries had unexpectedly low TEA in 2014 (IT – the lowest in the sample, DE, PT). Similarly, lower LE or PHG appear in individual cases, while HALE is systematically weaker in certain countries (notably DK and FI in 2014 and 2019).

In 2014, Cluster 4 achieved the highest values in nearly all indicators except SPTM, where it showed the lowest rates. However, within this group, Malta displayed low TEA, Greece higher SPTM, and Luxembourg and Cyprus relatively low HCE. The cluster's strong performance became even clearer in 2019 and 2020, when it was reduced to only Ireland, Cyprus, and Luxembourg. These countries combined the highest TEA, relatively high LE and HALE (especially in IE), low SPTM, moderate HCE, and strong PHG (slightly lower in LU In 2021, only Luxembourg and Ireland remained in Cluster 3. Cyprus diverged during the COVID-affected period, with HALE increasing compared to the other two countries, but with a sharper decline in LE and a simultaneous rise in HCE (in contrast to the drop observed in Ireland and Luxembourg). In this respect, Cyprus more closely resembled the Cluster 1 countries.

In 2022, several other countries joined this group, including Cyprus, another small country – Malta, the Northern country – Norway, and two Southern countries – Italy and Greece. Although these countries differ in several indicators, common features of this group are high PHG values, lower HCE (except in Malta), higher HALE (except in Luxembourg), high LE (except in Greece and, to a lesser extent, Cyprus), and higher TEA (except in Italy – the second lowest value in the sample – as well as Malta and Greece). In summary, this was the best-performing cluster on average, since, unlike Cluster 1, it combined low HCE values with higher PHG and HALE values among the health status indicators.

Special groups are also represented by Cluster 3 in 2019 and 2020. In 2019, this group included both Northern and Southern countries, a small country – Malta – along with another advanced country – Germany. Although TEA values differ within this group (they are high only in Norway, Sweden, and Spain), the countries share relatively high HALE, LE, PHG, and HCE, and low SPTM (with Germany showing weaker performance across all indicators). Hence, this group was separated from Cluster 1, particularly due to its higher LE and HALE values. By contrast, Cluster 3 in 2020 was separated from Cluster 2, as it showed lower HALE values (especially with Bulgaria performing higher) but also generally higher LE and TEA values. As indicated above, Cluster 4 in 2021 and 2022 consisted of countries close to those in Cluster 2, with very weak results in almost all indicators, except for TEA, where tertiary educational attainment is exceptionally high in Lithuania.

To sum up, the basic division into Clusters 1 and 2 suggests a relationship between healthcare expenditure and tertiary education, on the one hand, and stronger performance in health status indicators – including lower preventable and treatable mortality – on the other. However, the exceptional cases represented by Clusters 3 and 4 often challenge this hypothesis. In the next step, we assess the compatibility of our results with four major classifications of healthcare systems.

4.2. Key findings and implications of the COVID-19 pandemic

The analysis period (2019–2022) directly encompasses the onset and primary phase of the COVID-19 pandemic, providing empirical evidence of its impact on the development of key SDG-related health indicators. The pandemic introduced substantial systemic shocks that affected population health status, healthcare resource allocation, and mortality patterns, resulting in notable shifts in the clustering of countries – particularly within the smaller, more volatile clusters (Clusters 3 and 4).

Despite these disruptions, the consistent division between the high-performing Cluster 1 (Western and Northern European countries) and the lower-performing Cluster 2 (Central and Eastern European countries) remained broadly stable. However, the composition of Clusters 3 and 4 became increasingly unstable and context-specific during 2019–2022, capturing countries with mixed profiles or those exhibiting unique responses to the public health crisis.

The pandemic's effects are most visible in the evolution of key indicators. Between 2014 and 2022, life expectancy (LE) declined in 13 countries and healthy life years (HALE) in 11. A pronounced COVID-related decline in LE occurred between 2020 and 2021, when decreases were recorded in 17 countries. The largest drops were observed across all Central and Eastern European member states and in Cyprus. Although partly dependent on GDP fluctuations, healthcare expenditure (HCE) as a share of GDP increased in all monitored countries in 2020 – most notably in Cyprus – while in 2022 only two countries (Slovenia and Slovakia) recorded minor additional increases. Similarly, HALE declined in many countries during the pandemic years – 14 in 2020, 13 in 2021, and 15 in 2022.

The share of people with good or very good perceived health (PHG) dropped sharply in 2021 and 2022 (in 18 and 19 countries respectively), likely reflecting both the physical and psychological consequences of the pandemic. Finally, the standardized preventable and treatable mortality (SPTM) indicator rose in nearly all countries in 2020 (except Denmark, Iceland, and Norway), having increased in only two countries in 2019 (Greece and Bulgaria). In 2021, SPTM decreased in just eight countries – mostly Northern (Sweden, Finland, Norway), Southern (Spain, Italy), two Benelux states (Luxembourg, Belgium), and Switzerland. In 2022, only three Northern countries (Iceland, Finland, and Norway) recorded increases, a delayed effect of prior developments. In contrast, nearly all new member states and most Southern countries experienced notable declines.

Regarding cluster composition, 2021 stands out: during the COVID-affected period, Cyprus diverged from other traditionally high-performing small states (Ireland and Luxembourg). Cyprus experienced a sharper decline in LE alongside a rise in HCE, aligning it more closely with the on-average slightly less advanced Cluster 1 countries in that year. Conversely, Ireland and Luxembourg recorded drops in HCE in 2021. In Ireland, this reduction in HCE coincided with the largest overall HCE decrease (3.29 p.p.) and the highest increase in LE in the sample between 2014 and 2021, as well as a marked drop in SPTM.

A comparison of pre-COVID (2014) and pandemic-period (2019–2022) data reveals fundamental stability in the main regional divide but pronounced instability within smaller, high- and low-performing clusters. This volatility underscores the systemic shock the pandemic imposed on European health systems, particularly by affecting health outcomes and resource allocation. The primary structural finding – the existence of two major clusters – remained consistent across the full 2014–2022 period:

- Cluster 1 (High-Performing): Western and Northern European countries, together with the non-EU states Norway (though assigned to Cluster 3 twice during the analyzed period), Iceland, and Switzerland. These countries are characterized by high life expectancy (LE), higher healthy life years (HALE) in several cases, low rates of preventable and treatable mortality (SPTM), greater healthcare expenditure (HCE), and higher tertiary educational attainment (TEA).
- Cluster 2 (Low-Performing): Central and Eastern European member states (mostly those that joined after 2004), consistently showing the weakest results across nearly all indicators – low HALE, LE, perceived health (PHG), HCE, and TEA, alongside high SPTM..

Hence, the pandemic primarily affected the smaller, dynamic clusters (3 and 4), amplifying existing disparities. High-performing outliers such as Cyprus temporarily converged toward the Cluster 1 average, while low-performing outliers such as Latvia and Lithuania formed a distinct group with significantly poorer objective and subjective health outcomes, despite traditionally high TEA values. Moreover, TEA values declined annually in Lithuania during 2020–2022 and in Latvia in 2020, with an especially sharp fall in Lithuania in 2021 (–1.9 p.p., the second largest in the sample), further weakening its sustainable development position.

In summary, the analysis for 2019–2022 demonstrates that the COVID-19 pandemic functioned as a stress test for health systems, revealing their vulnerabilities through declines in life expectancy and fluctuating healthcare expenditure. It led to temporary yet significant shifts in the cluster membership of several countries, especially among smaller and more volatile groups.

4.3. Analysis of the results in relation to the Health System Models

Healthcare typologies provide a systematic framework for comparing how countries finance, deliver, and organize healthcare. Böhm et al. (2013) distinguished five OECD system types that partly overlap with the Beveridge–Bismarck–Mixed classification. Reibling et al. (2019) expanded this perspective by introducing five institutional dimensions and clustering 29 OECD countries into five models. More recently, Di Gioacchino et al. (2024) analyzed 25 European countries on the basis of healthcare expenditure, funding mix, and care orientation, identifying five clusters. Together, these typologies offer complementary insights into the diversity of healthcare systems and their alignment with classical Beveridge and Bismarck models.

To deepen the interpretation, the empirical clusters (1–4) identified in this study are compared with these established classifications. This mapping highlights how the clusters correspond to traditional Beveridge–Bismarck divides (see Table 3), regulation- or supply-oriented systems, and more recent assessments emphasizing efficiency, sustainability, and resilience. Taken together, the classifications of Böhm et al. (2013), Reibling et al. (2019), and Di Gioacchino et al. (2024) provide the reference framework for evaluating the performance and positioning of the clusters constructed in this study.

Table 3. Health Care System Models in sample countries by financing and organization, source: (Joumard et al., 2010; Wendt, 2009; Böhm et al., 2013; author's elaboration)

System Type	Description	Country Abbreviations
Bismarck-type	Social health insurance, contributions-based; financing relies on social insurance contributions.	AT, BE, CZ, DE, FR, HU, LU, NL, PL, SK, SI, CH
Beveridge-type	Tax-funded, universal coverage via NHS or similar; healthcare provision mainly public.	CY, DK, FI, IE, IT, MT, NO, PT, ES, SE, UK
Mixed/Hybrid	Features of both Bismarck and Beveridge systems; financing and provision show elements of both.	EE, GR, IS, LV, LT

Table 4. Comparison of Healthcare System Typologies: classifications by Böhm et al. (2013), Reibling et al. (2019), and Di Gioacchino et al. (2024)

Study	System Type	Countries	Closest to Beveridge/Bismarck
Böhm et al. (2013)	1. **NHS** (tax-financed)	DK, FI, IS, NO, SE, PT, ES, UK	Beveridge
	2. **NHI** (single insurer, private provision)	AU, CA, IE, IT, NZ	Mixed / Beveridge
	3. **SHI** (Bismarck)	AT, DE, LU, CH	Bismarck
	4. **Etatist SHI** (state + societal financing, private provision)	BE, EE, FR, CZ, HU, NL, PL, SK, IL, JP, KR	Bismarck
	5. **Private Health System**	US	Private
	6. **Mixed special case**	SI	Mixed
Reib-ling et al. (2019)	1. **Supply & choice-oriented public systems**	AU, AT, BE, CZ, DE, FR, IE, IS, LU, SI	Bismarck
	2. **Performance & primary care-oriented public systems**	FI, JP, KR, NO, NZ, PT, SE	Beveridge
	3. **Regulation-oriented public systems**	CA, DK, ES, IT, NL, UK	Beveridge
	4. **Low-supply & low-performance mixed systems**	EE, HU, PL, SK	Bismarck
	5. **Supply & performance-oriented private systems**	CH, US	Private
Di Gioacchino et al. (2024)	1. **High HCE per capita, secondary care**	AT, CZ, BE, FR, DE, IS, CH	Bismarck / Beveridge or mixed (IS)
	2. **High HCE per capita, primary care**	DK, FI, NL, NO, SE, UK	Beveridge / Bismarck (NL)
	3. **Medium HCE per capita, primary care**	EE, ES, PT, IT, SI	Beveridge / Mixed
	4. **Low HCE per capita, secondary care**	GR, LT, LV, HU, PL, SK,	Bismarck / Mixed
	5. **High HCE per capita, secondary care; High duplicate voluntary health insurance**	IE	Beveridge

Note: SI = Slovenia is classified by Böhm et al. (2013) as an implausible combination (state provision with societal financing and regulation) but currently exists in the OECD context.

The traditional Beveridge–Bismarck classification can be insufficient, as clusters include countries with different healthcare system models across the years. Therefore, three additional classifications described in Section 2 are considered: those of Böhm et al. (2013), Reibling et al. (2019), and Di Gioacchino et al. (2024). Table 4 presents all countries from the original studies, not only those included in our sample.
Considering the evaluation in relation to our results, Cluster 1 often corresponds to advanced Bismarck systems (e.g., AT, BE, DE, FR, NL, SI) and Beveridge systems (e.g., DK, FI, UK). These correspond to the first three groups identified by Böhm et al. (2013). Italy, while included in the second group, also appears in other clusters. According to Di Gioacchino et al. (2024), countries from the first two groups dominate Cluster 1, while Italy belongs to the third group. Regarding Reibling et al. (2019), countries from the first three groups are included, along with Switzerland, which is classified in the fifth group in this typology (see Table 4).
Cluster 2 reflects post-socialist Bismarck-type or mixed systems (e.g., BG, CZ, HR, HU, RO, SK, PL). Along with Cluster 3 in 2014, which includes the Baltic states and Poland, Cluster 3 in 2020, which contains the majority of the Cluster 2 countries from previous years, and Cluster 4 in 2020 and 2021, these clusters correspond to Reibling's low-supply/low-performance group (group 5), often align with Böhm's Etatist SHI, and are frequently included in Di Gioacchino's group 4.
Cluster 4 in 2014 combines Di Gioacchino's group 1 mixed (IS), group 2 Beveridge (NO, SE), group 3 Beveridge, and group 4 mixed systems (ES, GR, respectively), along with small advanced states (LU, MT, CY, IE). Three small high-performing states (CY, LU, IE) are also included in the next two years. As regards Böhm's classification, the first group (IS, NO, SE) and the second group (IE) are especially represented, while these countries are also part of the first three groups of Reibling's classification. Although in Cluster 3 in our analysis, the composition of countries is similar to that in Cluster 4 in 2022, with some changes in countries, it is even more variable according to the four analyzed classifications.
To sum up, Cluster 1 merges the advanced Beveridge and Bismarck systems with high healthcare expenditure (HCE) per capita and as a share of GDP, while Cluster 2 generally includes Bismarck or mixed/hybrid systems with lower HCE per capita and as a share of GDP, corresponding to group 4 in both Di Gioacchino's and Reibling's classifications. The same applies to Cluster 3 in 2020. Czechia appears in Cluster 3 in 2020. It must be emphasised that due to its higher HCE values it falls into group 1 in both Di Gioacchino's and Reibling's classifications. Clusters 4 in 2021 and 2022 follow a similar pattern. Less advanced countries typically apply Bismarck or mixed systems, whereas among more advanced countries there is substantial variability.
Ireland stands out as the most successful country toward the SD path in this field, frequently forming a small group of higher-performing countries. Luxembourg is a very small country with extraordinary conditions, while Cyprus ranks second; its performance in life expectancy declined after the COVID period, and it also has a higher HCE-to-GDP ratio than Ireland. Ireland's distinctiveness is partly due to high voluntary duplicate health insurance, as analyzed by Di Gioacchino et al. (2024).

5. Conclusions

The aim of this study was to explore similarities and differences in healthcare system performance among EU member states, the United Kingdom, Norway, Iceland, and Switzerland using cluster analysis of key indicators of health status, mortality, educational attainment, and healthcare expenditure. The analysis covered the years 2014 and 2019–2022 and enabled comparisons with established healthcare system classifications.
The results confirm a persistent division into two main groups. Cluster 1 consistently merges advanced Beveridge- and Bismarck-type systems – mostly in Western and Northern Europe – with higher healthcare expenditure per capita, stronger educational attainment, and better population health outcomes (life expectancy, healthy life years, perceived health, and lower preventable and treatable mortality). Cluster 2 generally includes post-socialist Bismarck or mixed systems from Central and Eastern Europe, characterized by lower healthcare expenditure and systematically weaker outcomes. Since Lithuania and Latvia were often separated from Cluster 2 as countries with particularly high levels of tertiary education but relatively poor health outcomes, we cannot fully confirm our hypothesis, but we can assume that this feature may help them progress toward the overall SD path.
Smaller clusters emerged in certain years. Ireland repeatedly stood out as a high-performing outlier, often forming a distinct small cluster due to strong outcomes relative to moderate expenditure – partly linked to its high rate of duplicate voluntary health insurance (Di Gioacchino et al., 2024). Luxembourg and Cyprus also appeared in separate clusters: Luxembourg reflecting the conditions of a very small, high-income state, and Cyprus showing a post-COVID-19 decline in life expectancy combined with a high healthcare expenditure-to-GDP ratio.
The COVID-19 pandemic acted as a structural stress test, temporarily reshaping the composition of several clusters. Between 2019 and 2022, most countries experienced declining life expectancy and healthy life years, rising healthcare expenditure, and reduced perceived health. The regional divide between high- and low-performing groups persisted, yet smaller clusters became highly unstable. In particular, Cyprus diverged from other high-performing small states during the pandemic. These observations underline the importance of system resilience and adaptability under stress conditions.

The empirical clusters correspond closely with established classifications of healthcare systems. High-performing clusters overlap with the advanced Beveridge and Bismarck groups identified in earlier research. In Böhm et al. (2013), these correspond to strong Social Health Insurance (SHI) and National Health Service (NHS) types; in Reibling et al. (2019), to the high-capacity systems; and in Di Gioacchino et al. (2024), to clusters with higher expenditure levels and balanced funding mixes. Conversely, weaker clusters align with low-supply models, particularly in Central and Eastern Europe. In this regard, our hypothesis about healthcare expenditure is confirmed to some extent, as also reflected in the division of countries into Clusters 1 and 2. Nevertheless, the experience of smaller high-performing countries partly contradicts the hypothesis – particularly in the case of Cyprus – while Ireland combines lower healthcare expenditure as a share of GDP with higher per capita values. It should be noted that not only the overall level of expenditure, but also its structure, is important (see Drastichová & Filzmoser, 2020).

In final conclusion, healthcare performance across the analyzed EU and EEA countries remains uneven, with persistent regional disparities. Advanced Beveridge and Bismarck systems are consistently associated with better health outcomes, while mixed or low-supply systems continue to lag behind, undermining progress toward sustainable development. Convergence toward higher-performing systems will require targeted investment in education, prevention, and the efficient use of healthcare resources. The experience of smaller countries, particularly Ireland, demonstrates that efficiency and institutional design can deliver strong results even with moderate levels of spending.

A key challenge for future research is to assess healthcare system efficiency and sustainability with a stronger focus on preventive care and long-term resilience, using advanced methods such as Data Envelopment Analysis (DEA). Future studies should also examine the interactions among different Sustainable Development Goals (SDGs) to support coherent and equitable progress in health, education, and social well-being across Europe.

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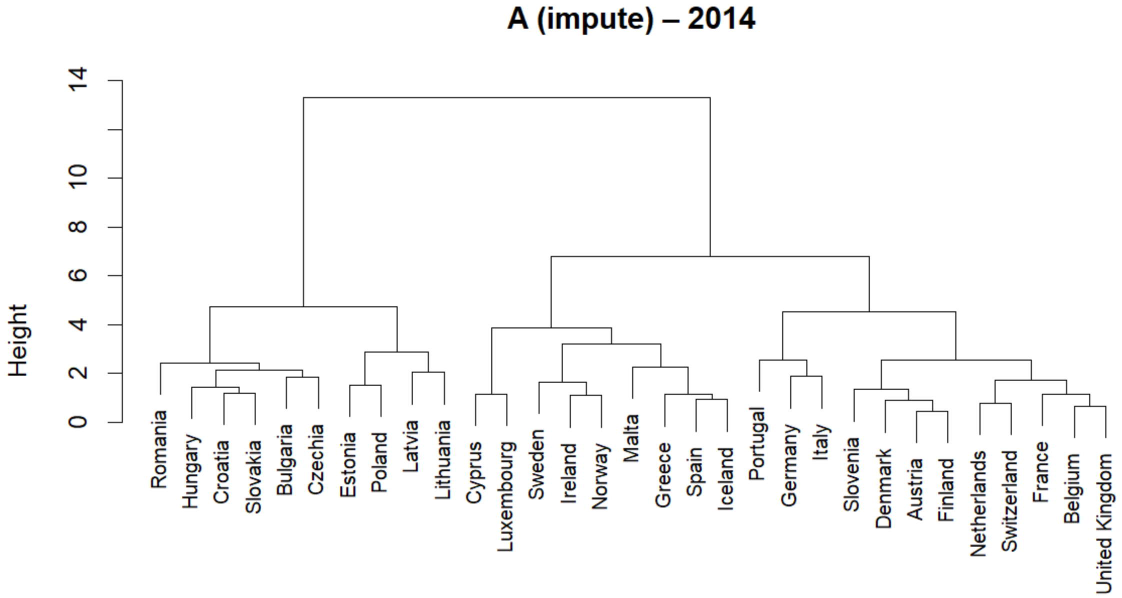
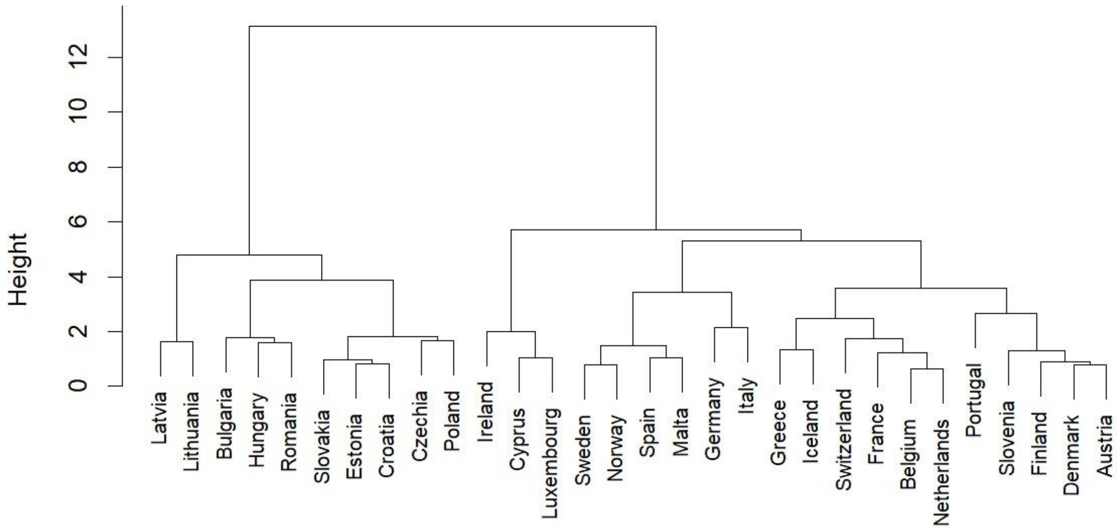
Annex

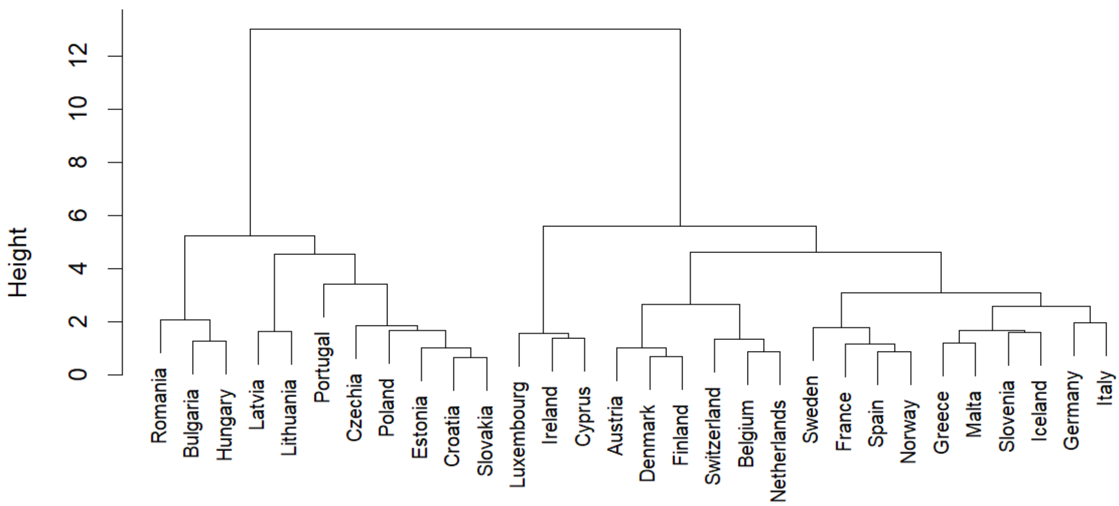
Figure 1. Dendrograms generated for the years 2014 and 2019–2022, source: author's elaboration using R statistical software

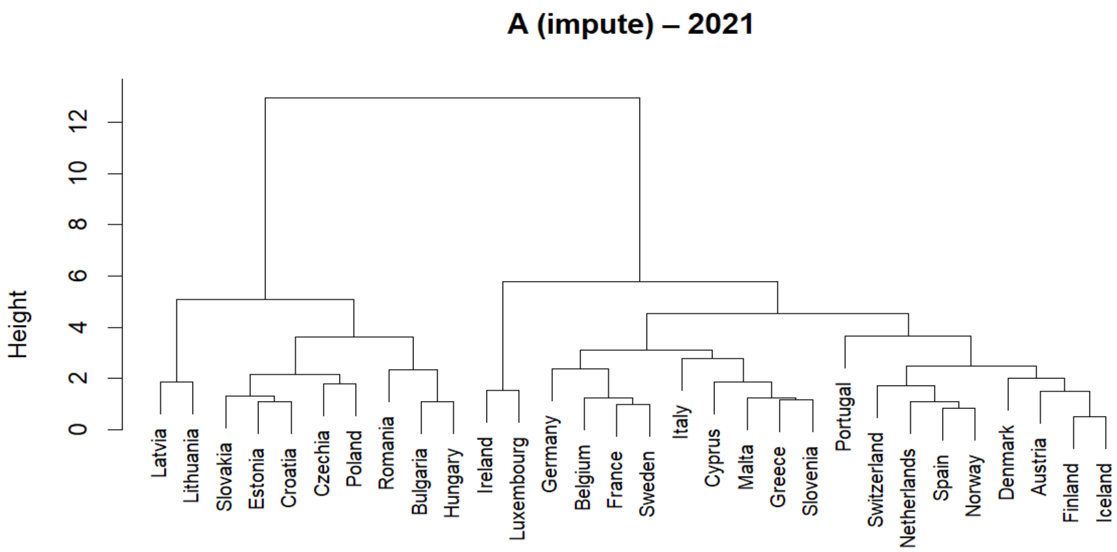


A (impute) – 2019



A (impute) – 2020





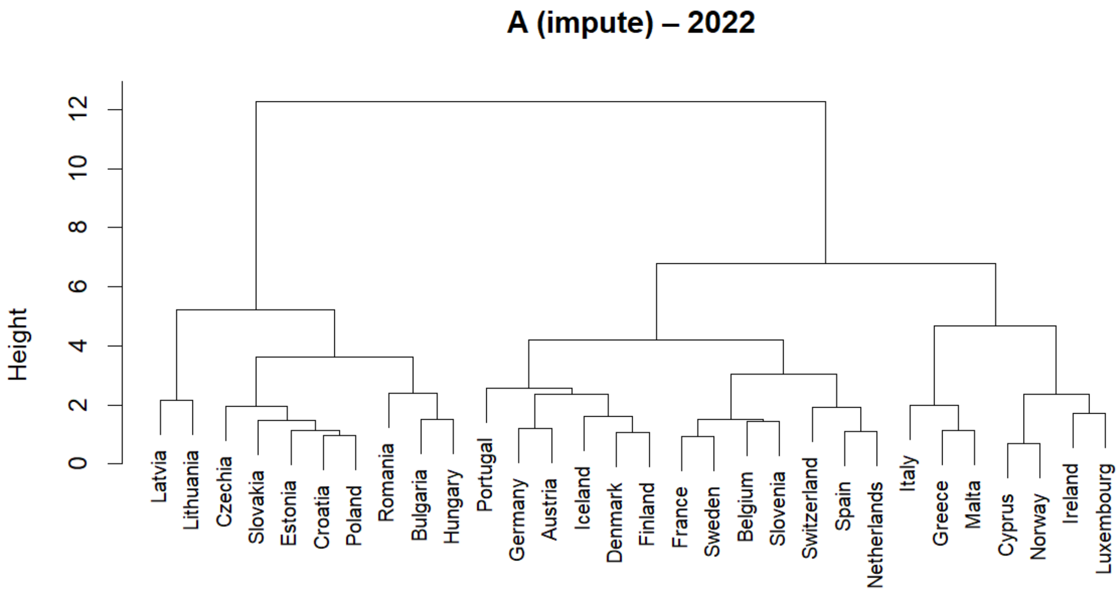


Table 5. Statistics for the created clusters, Source: author's elaboration using R statistical software

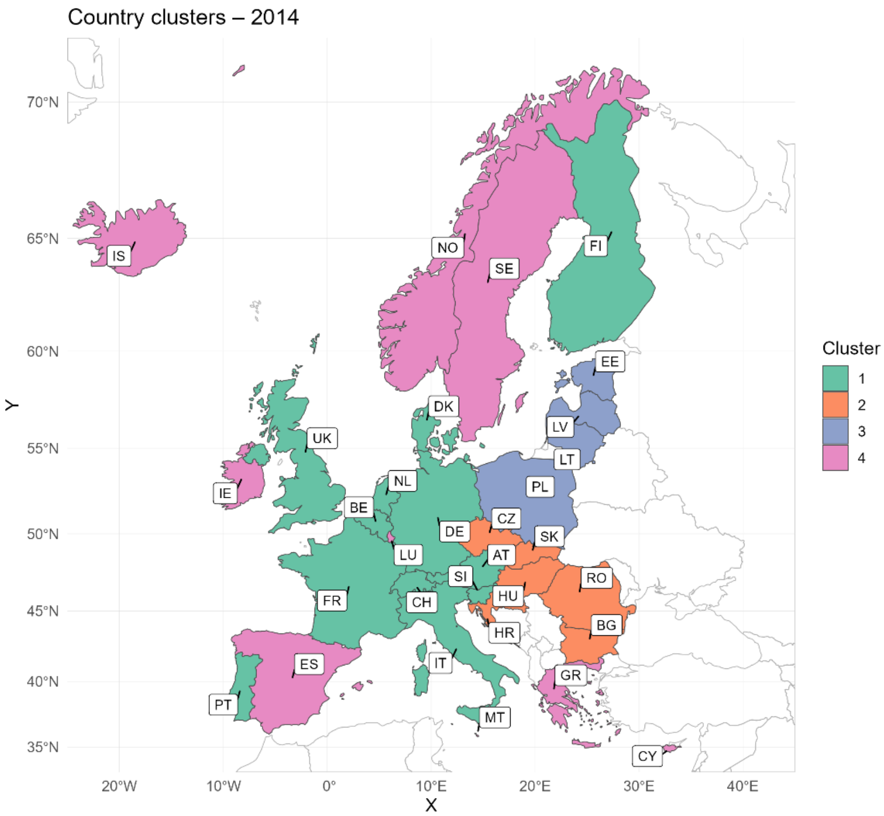
Year	Cluster	Indicator	mean	sd	n
2014	1	HALE	60,23333333	2,813711019	12
2014	1	HCE	10,11833333	0,848247748	12
2014	1	LE	81,775	0,863528701	12
2014	1	PHG	68,7	8,360295776	12
2014	1	SPTM	226,885	31,39599062	12
2014	1	TEA	38,775	7,083030297	12
2014	2	HALE	60,23333333	3,405681527	6
2014	2	HCE	6,788333333	0,955979428	6
2014	2	LE	76,55	1,700294092	6
2014	2	PHG	62,63333333	4,78274677	6
2014	2	SPTM	437,8833333	73,37004829	6
2014	2	TEA	30,13333333	2,549248255	6
2014	3	HALE	57,4	3,712142239	4
2014	3	HCE	6,105	0,297713509	4

Year	Cluster	Indicator	mean	sd	n
2014	3	LE	76,1	1,74164673	4
2014	3	PHG	50,25	6,188430065	4
2014	3	SPTM	473,015	96,89728324	4
2014	3	TEA	43,8	6,013318551	4
2014	4	HALE	68,04444444	3,665757463	9
2014	4	HCE	8,427777778	1,637481128	9
2014	4	LE	82,24444444	0,600231437	9
2014	4	PHG	76,43333333	3,251538098	9
2014	4	SPTM	204,2577778	20,74508784	9
2014	4	TEA	45,42222222	7,887296396	9
2019	1	HALE	60,8	2,824889378	11
2019	1	HCE	9,829090909	1,109589605	11
2019	1	LE	82,3	0,77588659	11
2019	1	PHG	70,69090909	8,339718766	11
2019	1	SPTM	204,6763636	29,17391653	11
2019	1	TEA	45,42727273	4,195257062	11
2019	2	HALE	59,27	3,947446432	10
2019	2	HCE	6,71	0,498442017	10
2019	2	LE	77,21	1,520562761	10
2019	2	PHG	59,42	8,003582531	10
2019	2	SPTM	414,454	68,52464005	10
2019	2	TEA	38,04	8,517720091	10
2019	3	HALE	70,13333333	2,744206018	6
2019	3	HCE	9,901666667	1,196284526	6
2019	3	LE	82,96666667	0,935236156	6
2019	3	PHG	72,76666667	3,788227378	6
2019	3	SPTM	183,05	24,78989552	6
2019	3	TEA	40,91666667	8,609626395	6
2019	4	HALE	64,9	4,070626487	3
2019	4	HCE	6,35	0,790506167	3
2019	4	LE	82,6	0,264575131	3
2019	4	PHG	77,73333333	6,232442004	3
2019	4	SPTM	184,94	11,43442609	3
2019	4	TEA	56,86666667	1,965536398	3
2020	1	HALE	64,36875	4,455216979	16
2020	1	HCE	10,755	1,038267788	16
2020	1	LE	81,94375	0,819730647	16
2020	1	PHG	73,50625	4,778768147	16
2020	1	SPTM	209,5075	31,28371728	16
2020	1	TEA	44,86875	6,452257357	16
2020	2	HALE	62,66666667	2,85365263	3
2020	2	HCE	7,293333333	1,116348213	3
2020	2	LE	74,33333333	1,106044002	3
2020	2	PHG	67,26666667	5,472050195	3
2020	2	SPTM	550,8766667	36,65411346	3

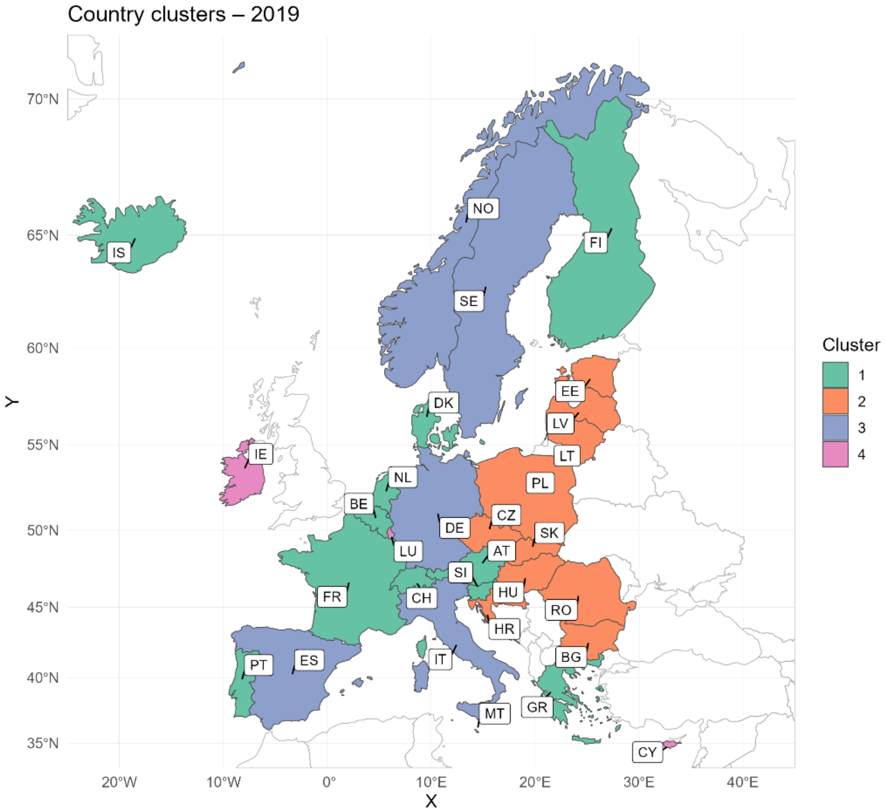
Year	Cluster	Indicator	mean	sd	n
2020	2	TEA	29,66666667	4,259499188	3
2020	3	HALE	58,325	2,883326452	8
2020	3	HCE	7,8825	1,281135099	8
2020	3	LE	77,55	2,047297871	8
2020	3	PHG	57,2125	7,787982959	8
2020	3	SPTM	403,70625	97,18878976	8
2020	3	TEA	41,8625	6,844379863	8
2020	4	HALE	64,13333333	1,800925688	3
2020	4	HCE	7,116666667	1,449045663	3
2020	4	LE	82,36666667	0,152752523	3
2020	4	PHG	78,53333333	5,522982286	3
2020	4	SPTM	196,2066667	14,21617858	3
2020	4	TEA	58,8	1,637070554	3
2021	1	HALE	63,65	3,400864942	18
2021	1	HCE	10,56277778	1,190036112	18
2021	1	LE	82,03333333	1,038664301	18
2021	1	PHG	71,13333333	6,792469879	18
2021	1	SPTM	215,0038889	36,00007731	18
2021	1	TEA	46,66111111	7,351121474	18
2021	2	HALE	60,0125	2,858289948	8
2021	2	HCE	7,635	0,963757527	8
2021	2	LE	74,8875	2,15634446	8
2021	2	PHG	65,4625	4,207115571	8
2021	2	SPTM	548,98375	116,0205932	8
2021	2	TEA	35,7625	6,22688583	8
2021	3	HALE	64,6	3,676955262	2
2021	3	HCE	5,99	0,537401154	2
2021	3	LE	82,5	0,282842712	2
2021	3	PHG	79,1	3,676955262	2
2021	3	SPTM	202,47	21,42533547	2
2021	3	TEA	62,4	0,282842712	2
2021	4	HALE	55,7	2,687005769	2
2021	4	HCE	8,57	1,187939392	2
2021	4	LE	73,65	0,777817459	2
2021	4	PHG	48,85	1,343502884	2
2021	4	SPTM	614,495	41,76879756	2
2021	4	TEA	51,5	8,485281374	2
2022	1	HALE	61,24615385	3,291305563	13
2022	1	HCE	10,46538462	1,032784387	13
2022	1	LE	81,96923077	0,888242286	13
2022	1	PHG	67,36923077	7,18521452	13
2022	1	SPTM	207,17	30,36668597	13
2022	1	TEA	47,07692308	5,790243784	13
2022	2	HALE	61,175	2,890254561	8
2022	2	HCE	7,10375	0,8518373	8

Year	Cluster	Indicator	mean	sd	n
2022	2	LE	76,7875	1,59592114	8
2022	2	PHG	65,25	4,702886652	8
2022	2	SPTM	424,37375	71,99177888	8
2022	2	TEA	35,8125	5,977681705	8
2022	3	HALE	66,31428571	3,041616112	7
2022	3	HCE	7,732857143	1,390991424	7
2022	3	LE	82,22857143	0,771825295	7
2022	3	PHG	76,01428571	2,618796525	7
2022	3	SPTM	198,4585714	26,24652512	7
2022	3	TEA	50,81428571	12,33753468	7
2022	4	HALE	57,25	4,313351365	2
2022	4	HCE	7,67	0,608111832	2
2022	4	LE	75,15	0,919238816	2
2022	4	PHG	49,15	1,48492424	2
2022	4	SPTM	517,975	35,85738487	2
2022	4	TEA	52,05	8,697413409	2

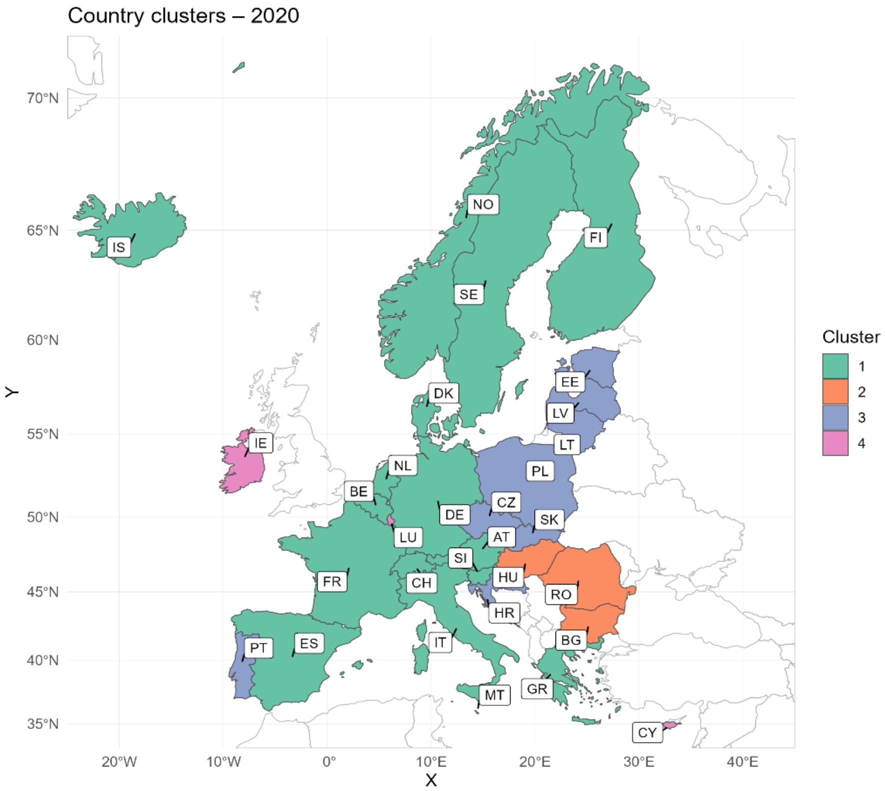
Map 1. Clusters identified in 2014, source: author's elaboration using R statistical software



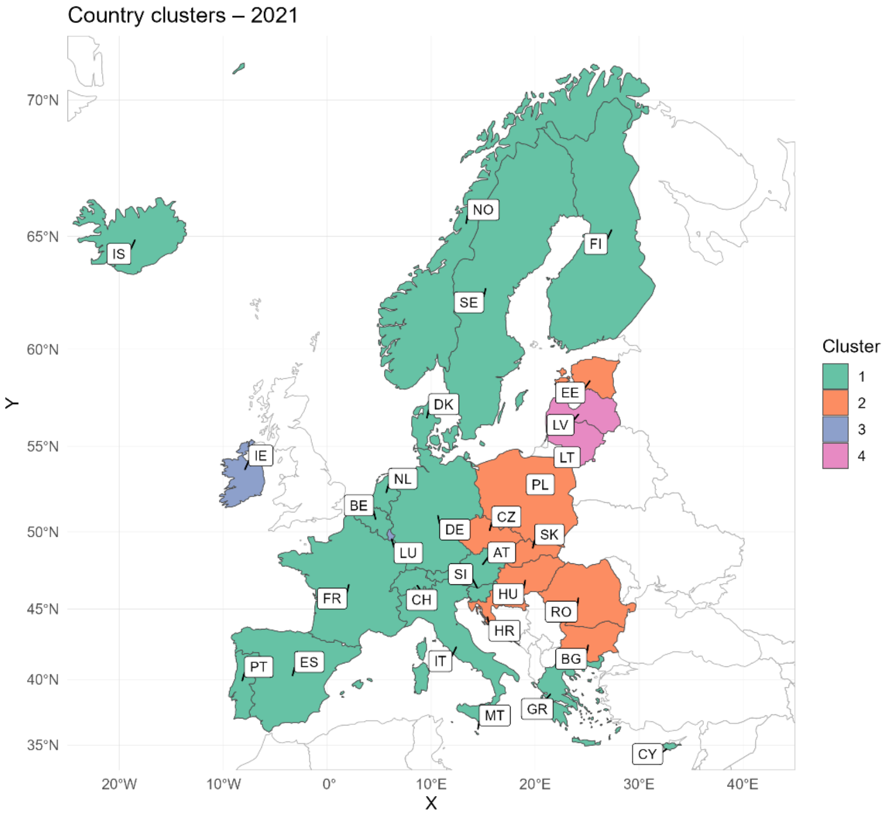
Map 2. Clusters identified in 2019, source: author's elaboration using R statistical software



Map 3. Clusters identified in 2020, source: author's elaboration using R statistical software



Map 4. Clusters identified in 2021, source: author's elaboration using R statistical software



Map 5. Clusters identified in 2022, source: author's elaboration using R statistical software