

Article

Mapping Healthcare System Complexity in the European Union: A Perspective on Resources, Determinants, and Outcomes

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Abstract

The transformation of healthcare systems presents a key challenge for EU Member States, as they face growing population needs, resource pressures, and ongoing health disparities among communities. Using a systems-thinking approach provides a suitable framework for analyzing how healthcare resources, behavioral and social health determinants, and overall population outcomes are interconnected. This study aims to explore these relationships from a systemic viewpoint within health communities across the European Union. The research employs a cross-sectional approach, utilizing aggregated data from all 27 EU Member States. It involves descriptive and factor analyses to create composite indices of healthcare resources, positive health determinants, and health outcomes. Furthermore, it uses a univariate Generalized Linear Model (GLM) and multilayer perceptron neural networks to model nonlinear relationships among variables. Cluster analysis is also conducted to classify Member States into different health performance typologies. The results emphasize connections between healthcare system resources and population health outcomes, illustrating how positive determinants impact health status and highlighting structural differences across European communities. The results indicate relevant associations between healthcare system resources and population health outcomes, whereas the analysis of positive health determinants suggests more complex, partly nonlinear patterns. The findings also highlight structural differences across European health communities.

Keywords: healthcare resources; health determinants; population health outcomes; systems thinking; European Union; artificial neural networks; health clusters



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1. Introduction

Healthcare systems in the European Union are undergoing continuous change due to significant demographic shifts, a transition towards more chronic diseases, and growing pressures on financial and human resources. In this environment, health performance

cannot be fully understood by examining only individual indicators, such as spending or service access. Instead, it requires a comprehensive view that considers how system resources, behavioral and social factors, and population outcomes are interconnected. Recent research emphasizes that health outcomes result from complex adaptive systems, which involve nonlinear interactions, feedback mechanisms, and adaptive processes that exceed the reach of traditional analysis methods [1,2].

The systems thinking approach has become increasingly important as a framework for analyzing healthcare systems, providing theoretical and methodological tools to understand the complex interactions among their components [3,4]. In the European Union, where different institutional models and levels of socioeconomic development exist, this perspective is especially useful for explaining ongoing health disparities, despite shared goals and similar policy efforts [5,6]. Research indicates that the link between healthcare resources and population health outcomes is heavily influenced by contextual factors, governance, and individual and collective behaviors, revealing the shortcomings of purely linear or sector-specific methods [7–12].

Despite these theoretical advances, important gaps remain in the literature. Many studies still analyze healthcare system resources, behavioral factors, or population outcomes in isolation, rather than integrating them into a unified systemic framework [5]. In addition, traditional linear models dominate empirical research, capturing average effects but failing to capture nonlinear interactions and feedback mechanisms specific to complex systems [11]. Furthermore, comparative studies across the European Union often focus on the convergence or divergence of individual indicators, while overlooking the identification of structural typologies that emerge from the interaction among resources, determinants, and outcomes [13].

Building on these gaps, this article examines healthcare systems in the European Union from a systemic perspective by combining institutional resources, positive health determinants, and population outcomes into a unified analytical framework. The research employs a mix of quantitative techniques, such as factor analysis to create composite variables, generalized linear models to assess average effects, artificial neural networks to identify nonlinear patterns, and cluster analysis to categorize Member States into typologies. The novelty of this work lies in its integrated use of these methods within a systems-thinking approach that examines health as being associated with complex configurations among subsystems and highlights exploratory health-performance across Europe.

The article is organized as follows: the next section outlines the theoretical framework and develops the research hypotheses, and the following section describes the data and methods. The following section presents the empirical results, which are then discussed in relation to the existing literature. The article concludes with remarks on implications for public policy and future research.

2. Literature Review and Hypotheses Development

2.1. Health Systems as Complex and Adaptive Systems: A Systems Thinking and Community Perspective

Modern literature increasingly views healthcare systems as complex adaptive systems, marked by numerous interdependencies, nonlinear feedback loops, and emergent behaviors that traditional sectoral analysis cannot fully explain [1,2]. This shift underscores the understanding that health outcomes are not the result of a single intervention but rather stem from the interplay among institutional actors, resources, individual actions, and broader social and economic factors [14,15].

The systems thinking approach provides an integrative analytical framework that overcomes the traditional fragmentation of health policies and facilitates an understanding

of how decisions within one subsystem can generate indirect or unintended effects across other system components [3,4]. From this perspective, healthcare systems function not merely as providers of medical services, but as socio-institutional ecosystems in which population health emerges from the interaction of governance, financing, service organization, and social and behavioral determinants of health [16–18].

The World Health Organization has been pivotal in redefining health systems as a collection of organizations, individuals, and actions dedicated to promoting, restoring, or maintaining health [16]. This approach highlights that evaluating health system performance requires more than just medical output metrics; it also involves assessing how well the system responds to population needs, utilizes resources effectively, and addresses health disparities [6,12,19–21].

In European literature, scholars often use systemic perspectives to explain why health performance varies persistently across Member States, despite shared goals and similar institutional frameworks [8,22]. Comparative research shows that merely increasing healthcare spending does not necessarily lead to better population health unless it is supported by effective coordination, governance, and service integration mechanisms [11,13,23–26]. This evidence underscores that the link between system resources and health outcomes depends heavily on the healthcare system's overall structure and its functioning.

The community aspect is central in the systemic approach to health and is essential for the sustainable transformation of healthcare systems [6,27]. Health communities, networks of public, private, and civic actors involved in health promotion at local or regional levels, serve as the ground on which health policies translate into practical actions and where the interplay of structural and behavioral factors becomes evident [28,29]. From this viewpoint, healthcare systems are deeply connected to the social contexts in which they operate, and their success relies heavily on mobilizing community resources and fostering trusting relationships between providers and beneficiaries.

A substantial body of research demonstrates that social determinants of health, such as educational attainment, social integration, and community support, significantly influence both individual health-related behaviors and population-level outcomes [30,31]. These effects are often mediated by the structure of the healthcare system and by its interactions with other social systems, including education, social protection, and labor markets [5,32]. Consequently, a systemic approach requires recognizing intersectorality as a fundamental principle of health policy.

The conceptualization of health as an emergent outcome of a complex system is supported by the literature on large-scale transformations in healthcare systems. Realist review analyses show that successful reforms rarely follow linear or predictable trajectories; instead, they unfold as iterative processes shaped by context, leadership, and the adaptive capacity of the involved actors [27]. Within this framework, scholars view healthcare systems as dynamic entities capable of learning and adapting, yet vulnerable to external shocks and internal dysfunctions [2].

2.2. Healthcare Resources and Population Health Outcomes in the European Union

The specialized literature consistently emphasizes the crucial role of healthcare system resources in influencing population health outcomes. However, the link between institutional inputs and health outcomes is complex and not straightforward. In the European Union, this connection varies significantly across Member States, with notable differences in healthcare spending, the distribution of human resources, and the organization of long-term care services [12,22,23].

Health expenditure is often used in economic studies as an indicator of a healthcare system's ability to provide adequate services to its population. Early research indicated a

positive association between expenditure and measures such as life expectancy. However, later studies revealed that this relationship is influenced by institutional, demographic, and macroeconomic factors [23,33–35]. Data from OECD and European Union sources, particularly Eurostat and OECD Health Statistics, indicate that regions with similar spending levels can have markedly different health outcomes, underscoring the importance of efficiency and governance in shaping this relationship [23,33,35].

A key area of the existing literature examines whether healthcare expenditure converges or diverges across the European Union. Multiple empirical studies point to long-term trend convergence, especially among older Member States; however, these developments are often partial and sometimes show divergence, notably during economic downturns [13,36,37]. Analyses using unit root and cointegration tests indicate that, while healthcare spending generally tends to “catch up” over time, the pace of this convergence is influenced by the countries’ financing mechanisms and their ability to maintain steady growth in health investments [23,24,38,39].

In addition to the financial aspect, the literature highlights the critical role of human resources in health, particularly the availability of medical personnel, as a key factor influencing the effectiveness of the healthcare system. The quantity and regional distribution of physicians are linked to access to services, care quality, and, indirectly, population health results [40–42]. Within the European Union, variations in medical workforce density mirror wider disparities in economic and institutional development, leading to ongoing inequalities in health outcomes [5].

A specific part of the literature examines the significance of long-term care, particularly in the context of population aging in Europe. Increasing life expectancy and the rise of chronic diseases are placing additional strain on healthcare systems, making long-term care a vital component of overall resources [43,44]. Research shows that investing in this area can enhance quality of life and lessen hospital workload; however, the effects on traditional health metrics depend on how well it is integrated with other parts of the healthcare system [6,20,45,46].

Researchers frequently examine the link between healthcare system resources and population health outcomes using aggregated indicators like life expectancy or healthy life years. While these measures offer a broad overview of system performance, the literature warns about their limitations, especially in detecting short-term changes and accounting for cultural or social differences [47]. Moreover, although widely used, mortality-based indicators can be unidimensional and sometimes serve as inappropriate proxies for healthcare effectiveness, particularly for elective, non-life-saving procedures such as joint arthroplasty, where quality-of-life improvements are more relevant than survival outcomes. Recent studies highlight the importance of employing multiple, complementary indicators that reflect both quantitative and qualitative aspects of health status [48,49].

Econometric and statistical research confirms that the relationship between healthcare resources and health outcomes is complex and often nonlinear [11]. Endogenous growth models posit threshold effects, in which additional investments in health yield varying marginal returns depending on the system’s initial level of development [50,51]. Additionally, economic shocks, such as recessions, can temporarily alter this relationship by increasing vulnerabilities in systems with weaker financing structures [52].

2.3. Positive Health Determinants and Multidimensional Health Outcomes

Beyond healthcare system resources, specialized literature highlights the importance of positive health determinants in shaping population health outcomes, especially in developed societies facing high rates of chronic and non-communicable diseases. These determinants encompass individual behaviors, social factors, and living conditions that

directly or indirectly affect health status and a population's ability to utilize healthcare resources effectively [12,29,30,53].

A large body of research underscores the importance of physical activity for health, with well-established effects on all-cause mortality, cardiovascular health, and mental well-being [54,55]. According to World Health Organization guidelines, maintaining sufficient physical activity levels can prevent many non-communicable diseases and also promote longer life expectancy and healthier years [56]. However, the distribution of physical activity across populations is uneven and influenced by socioeconomic, cultural, and environmental factors, resulting in ongoing disparities among states and communities [4].

Healthy nutrition is a key positive factor, with proven impacts on reducing the risks of cardiovascular disease, diabetes, and obesity. Epidemiological research shows that diets high in fruits and vegetables are associated with lower rates of premature death and better quality of life [57,58]. However, these benefits depend on economic access, education, and supportive public policies. This indicates that researchers must consider behavioral factors within the broader social and institutional environment rather than analyze them in isolation [33].

Maintaining a normal body mass index (BMI) is closely linked to physical activity and dietary habits, serving as a combined indicator of energy balance and overall health. Research highlights obesity as a significant risk factor for various chronic diseases. It shows that its prevalence reflects both personal behaviors and social and economic factors. Consequently, comparative studies often use BMI-related metrics as indicators of healthy or unhealthy lifestyles in cross-country analyses [48,58].

Behaviors related to tobacco and alcohol use are key factors influencing health. The research consistently shows that smoking increases the risk of death and illness, while quitting smoking offers significant health benefits [59]. Likewise, alcohol intake is linked to various health problems, and recent research highlights the importance of preventive strategies and comprehensive public policies to reduce its effects [60]. However, the links between these behaviors and health outcomes are often nonlinear and involve threshold effects, making their analysis more complex [61].

A noticeable and growing focus in the recent literature has been on social support and community integration. Both classical and modern research indicate that strong social ties correlate with lower mortality rates and improved health outcomes, with effect sizes similar to those of well-known health behaviors [11,31,62]. Social support influences health through direct means, such as reducing stress, and indirect pathways, including encouraging healthy habits and enhancing access to healthcare resources [32].

The literature on multidimensional health outcomes underscores the need to move beyond unidimensional indicators, such as life expectancy, toward measures that capture both the quantity and quality of life. Concepts such as healthy life years and self-perceived health provide a more comprehensive perspective on population well-being by integrating physical, psychological, and social dimensions [47]. Empirical evidence indicates that positive health determinants influence these outcomes in differentiated ways, with more pronounced effects on subjective dimensions of health [5].

A common theme in the literature emphasizes the context-dependent and interconnected nature of positive health determinants. Health behaviors are not just individual choices; they are influenced by social norms, public policies, and economic systems, leading to complex interactions across multiple levels [30,31]. This complexity is why straightforward linear models often cannot fully describe the relationships between positive determinants and health outcomes, underscoring the need for analytical methods that can detect nonlinear effects and interactions among factors [3,4].

2.4. Methodological Approaches in Health System Analysis and Hypotheses Development

The complexity of healthcare systems, as discussed earlier, has led to a major shift in the methods used to analyze the connections among resources, determinants, and health outcomes. Experts agree that simple univariate or purely descriptive methods cannot fully capture the complex, interrelated nature of these relationships, especially in comparative settings like the European Union [1,4].

2.4.1. Dimensionality Reduction and Latent Constructs in Health System Research

An initial approach to address this complexity involves using dimensionality-reduction techniques such as factor analysis and principal component analysis (PCA). These methods help identify latent constructs that combine information from many correlated indicators, making interpretation and comparison easier [63]. In healthcare system research, PCA is commonly used to create composite indices of resources, determinants, or health performance, thereby reducing multicollinearity and improving the robustness of subsequent analyses [41,64,65].

Research indicates that latent constructs more accurately reflect systemic realities than isolated indicators. For example, healthcare resources such as expenditure, personnel, and infrastructure are rarely independent; they are closely linked through institutional and financial mechanisms [12,26,40,53,66]. Likewise, positive health factors often group into behavioral and social patterns, while health outcomes encompass both objective and subjective aspects of well-being [5,47]. These insights robustly support the development of the first research hypothesis.

Hypothesis H1. *Indicators associated with healthcare system resources, positive health determinants, and health outcomes form separate, coherent latent constructs. This reflects the multifaceted and interconnected nature of healthcare systems within the European Union.*

2.4.2. Linear Modeling and Average Effects in Comparative Health Analysis

Generalized Linear Models (GLMs) are among the most common methods for examining how inputs into the healthcare system relate to population health outcomes, especially in cross-country studies. The economics and public policy fields often use these models to estimate average effects while accounting for differences across units of analysis [8,22]. GLMs offer significant benefits in interpretability and statistical inference, making them ideal for testing hypotheses about the direct links between resources and health outcomes.

Nonetheless, extensive research underscores the limitations of linear models in capturing the complex dynamics of healthcare systems. Studies on expenditure convergence and the effects of health investments on life expectancy reveal relationships and effects that depend on the system's initial level of development [26,36,39]. Despite these challenges, the literature recognizes the usefulness of GLMs as a starting point for analysis, especially for evaluating average relationships at a population level [24]. This body of work underpins the second research hypothesis:

Hypothesis H2. *Healthcare resources and positive health determinants are positively associated with health outcomes in a generalized linear model across European Union Member States.*

2.4.3. Nonlinear and Machine Learning Approaches in Health Systems Research

Over the last ten years, research on healthcare systems has increasingly incorporated nonlinear methods and machine learning techniques, especially artificial neural networks (ANNs). These approaches are appreciated for their ability to model complex, nonlinear relationships and multiple-variable interactions without requiring predefined functional forms [61,67].

Theoretical considerations support the use of ANNs in population health analysis, given the adaptive and evolving nature of healthcare systems, in which the impact of resources or determinants depends on their specific combinations [3,4]. Empirical evidence shows that nonlinear models frequently outperform linear models in prediction accuracy, particularly when relationships include thresholds, saturation points, or synergistic factors [51,52].

In the context of positive health determinants, the literature suggests that the effects of healthy behaviors and social support on population outcomes do not follow strictly additive patterns, but instead depend on specific social and institutional contexts [6,31].

These findings underpin the third research hypothesis:

Hypothesis H3. *The relationships among healthcare resources, positive health determinants, and health outcomes may include nonlinear components that artificial neural network models can explore as a complement to traditional linear models.*

2.4.4. Typologies, Clustering, and Health System Performance

Another important methodological approach in comparative literature is cluster analysis for classifying types of states or healthcare systems. These techniques categorize units of analysis based on their structural or performance similarities, offering a perspective that complements causal evaluations [41,68]. In European research, scholars often use clustering methods to highlight unique regional or institutional variations, such as disparities in health outcomes between Western, Central, and Eastern Europe [5].

Cluster analysis is especially useful in a systems-thinking approach because it enables the detection of emergent patterns in healthcare systems without assuming unidirectional causality. By grouping states with comparable health performances, this method improves insight into how varying mixes of resources, determinants, and institutional settings lead to different population health outcomes [28]. This framework underpins the following hypothesis:

Hypothesis H4. *European Union Member States can be grouped into distinct typologies based on health outcomes, revealing structural differences in health performance and well-being across European communities.*

3. Materials and Methods

3.1. Research Design

This study uses a quantitative, cross-sectional approach to examine the complex relationships between healthcare system resources, positive health factors, and population health outcomes in EU Member States. It relies on a harmonized dataset from a single time point, ensuring direct comparability across countries and avoiding distortions caused by calendar differences or institutional changes over time. Data are sourced from official European sources, including the annual Eurostat databases and the most recent European Health Interview Survey (EHIS) wave from 2019, which offers standardized data on health status and behaviors.

The research design adopts a systems-thinking approach, viewing health as being associated with configurations of institutional, behavioral, and social factors. Given the cross-sectional nature of the dataset, the study does not aim to establish causal effects, but to identify statistical associations, latent structures, possible nonlinear patterns, and exploratory systemic typologies among EU Member States. This perspective supports the use of multiple quantitative methods to capture different dimensions of the system.

In the initial stage, descriptive analysis outlines how variables are distributed and highlights heterogeneity among Member States. Next, exploratory factor analysis simplifies the data by creating composite variables that represent healthcare system resources, positive health determinants, and population health outcomes. The study then examines the connections among these latent factors using a generalized linear model, allowing estimation of average effects and testing hypotheses about how resources and determinants affect health outcomes.

To explore possible nonlinear associations and systemic configurations among variables, the research design uses multilayer perceptron neural networks, applied separately to healthcare system resources and positive health determinants. In addition to these analyses, the study uses cluster analysis to classify Member States by health performance, revealing distinct configurations of European health communities in terms of population well-being.

By combining these methods within a coherent analytical framework, the research design enables an in-depth exploration of the complexity of European healthcare systems. It provides a solid basis for interpreting structural and functional differences among Member States.

3.2. Selected Data

The empirical analysis uses a harmonized European dataset that merges information from the annual Eurostat databases with indicators from the most recent wave of the European Health Interview Survey (EHIS) [69]. This choice is based on the high methodological comparability and comprehensive coverage of all 27 EU Member States. The 2019 data provide a clear snapshot of healthcare system resources, health behaviors, positive health determinants, and population health outcomes before the significant disruptions caused by the COVID-19 pandemic.

The dataset's structure embodies a multidimensional view of health, aligning with the systems-thinking approach used in this study. It captures healthcare system resources through indicators that reflect financial capacity, human resources, and care services—such as current healthcare expenditure in purchasing power standards, long-term care expenditure, and the total number of physicians at the national level. These measures provide a comprehensive overview of the institutional inputs into healthcare systems and are commonly used in comparative analyses across Europe.

Positive health determinants are measured through indicators reflecting healthy lifestyles and social capital. These include maintaining a normal body mass index, participating in physical activities that promote health, eating enough fruits and vegetables daily, not smoking, avoiding recent alcohol use, and experiencing high perceived social support. Collectively, these indicators represent behavioral and social aspects of health that the literature broadly acknowledges as crucial for prevention and enhancing population well-being.

Health outcomes are evaluated using indicators that include both objective and subjective aspects of health. These comprise healthy life years at birth, absolute life expectancy, and the percentage of people reporting good or very good self-perceived health. Using these variables enables the analysis to address lifespan, quality of life, and perceptions of personal health. This approach provides a more complete view of how well the healthcare system performs.

The study chose variables based on existing literature and the availability of comparable European data, ensuring relevance and avoiding redundancy. All variables were measured at the national level and underwent initial checks for distribution, outliers, and statistical consistency before use in the multivariate analyses (Table 1).

Table 1. Variables used in the analysis and data sources.

Variable	Dataset	Measure	References
CHE	Current health care expenditure	Purchasing power standard (PPS) per inhabitant	[70]
LTE	Long-term care (health)	Purchasing power standard (PPS) per inhabitant	[71]
PN	Physicians	Number	[72]
BMIN	Body mass index—normal	Percentage	[73]
PAT	Performing health-enhancing physical activity (Aerobic, muscle-strengthening, or both)	Percentage	[74]
DCFV5	Daily consumption of fruit and vegetables—5 portions or more	Percentage	[75]
STPNS	Smoking of tobacco products—Non-smoker	Percentage	[76]
FACN	Frequency of alcohol consumption—Never or not in the last 12 months	Percentage	[77]
OPSSS	Overall perceived social support—Strong	Percentage	[78]
HLYB	Healthy life years at birth	Year	[79]
LEB	Life expectancy in absolute value at birth	Year	[80]
GVGPH	Share of people with good or very good perceived health	Percentage	[81]

Source: developed by the author based on Eurostat [70–81].

3.3. Methods

The empirical analysis employs an integrated methodological framework that captures the complex, multidimensional nature of the healthcare systems under study. Consistent with a systems-thinking approach, the methods used do not aim to identify direct causal links. Instead, they estimate statistical associations, uncover latent structures, and explore possible systemic configurations among healthcare resources, positive health factors, and population health outcomes. In this study, the term “systemic interaction” is used in an interpretive sense, referring to the coexistence and configuration of institutional, behavioral, and social dimensions within national healthcare systems, rather than to causally identified interaction effects.

In the initial stage, the study performs descriptive analysis of the data to characterize variable distributions and the level of heterogeneity across European Union Member States. It calculates measures such as central tendency, dispersion, and distribution shape to evaluate whether the data are appropriate for further multivariate analyses and to detect potential outliers that might affect the results. This phase is exploratory and provides the statistical foundation for interpreting more complex analytical methods.

The study then uses an exploratory factor analysis with the principal components method to reduce the dataset’s dimensions and create meaningful synthetic variables [82]. This approach helps identify latent constructs that explain the shared variance among observed indicators, making it easier to interpret relationships across complex dimensions. The factor model can be expressed as follows:

$$x_i = \Lambda f_i + e_i \quad (1)$$

x_i —the vector of observed standardized variables for country i ;
 Λ —the matrix of factor loadings;
 f —the vector of latent factor scores;
 e_i —the vector of unique errors;
 i —the analyzed EU Member States.

The study evaluates the appropriateness of factor analysis using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett’s test of sphericity, and selects factors with eigenvalues greater than 1 [83]. The resulting factor scores are then used as synthetic variables in the explanatory models.

To examine the linear relationships among the latent constructs, the analysis employs a univariate generalized linear model, with population health outcomes as the dependent variable and healthcare system resources and positive health determinants as independent variables. The GLM specification can be written as follows:

$$Y_i = \beta_0 + \beta_1 HR_i + \beta_2 PHD_i + \varepsilon_i \quad (2)$$

Y_i —the factor score for population health outcomes in country i ;
 HR_i —the factor score for healthcare system resources;
 PHD_i —the factor score for positive health determinants;
 β_0 —the intercept;
 β_1, β_2 —the regression coefficients;
 ε_i —the error term.

This setup allows for estimating average effects and testing the statistical significance of relationships.

Given the evidence in the literature of nonlinear relationships and complex interactions within healthcare systems, the analysis also uses multilayer perceptron artificial neural networks. This approach effectively captures nonlinear relationships and threshold effects without requiring predefined functional forms [83]. The general structure of the ANN–MLP model can be expressed as follows:

$$\hat{Y}_{ik} = g_k \left(\alpha_{0k} + \sum_{h=1}^H \alpha_{hk} f_h \left(b_{0h} + \sum_{j=1}^H w_{jh} X_{ij} \right) \right) \quad (3)$$

$\hat{Y}_{ik}$ —the predicted value of the output variable k for country i ;
 g_k —the activation function of the output layer;
 α_{0k} —the output-layer bias;
 α_{hk} —the weight connecting the hidden neuron h to the output variable k ;
 f_h —the activation function of the hidden layer,
 w_{jh} —the weight connecting input variable j to hidden neuron h .
 X_{ij} —the value of the input variable j for country i .

In the empirical models estimated in this study, $H = 1$, consistent with the parsimonious ANN–MLP architecture selected for the small sample of 27 EU Member States.

The analysis considers two separate models: one that uses healthcare system resources as inputs and another that focuses on positive health determinants. This approach enables a comparison of how each dimension contributes to explaining population health outcomes. The study evaluates variable importance by examining each input’s role in decreasing prediction error.

The ANN–MLP procedure was implemented in IBM SPSS Statistics v.27 and designed as an exploratory nonlinear modelling stage rather than a purely predictive exercise. Before estimating the neural networks, the dataset was checked for missing values, distributional irregularities, and consistency across the 27 EU Member States. All cases with complete

information were retained in the analysis. Because the variables were measured on different scales, preprocessing included automatic rescaling in SPSS. In the first ANN–MLP model, which examined the relationship between healthcare system resources and health outcomes, the input covariates, namely current healthcare expenditure, long-term care expenditure, and the number of physicians, were standardized.

In contrast, the scale-dependent output variables, healthy life years at birth, life expectancy at birth, and self-perceived good or very good health, were normalized. In the second ANN–MLP model, which examined the relationship between positive health determinants and health outcomes, the input covariates, namely normal body mass index, physical activity, daily fruit and vegetable consumption, non-smoking status, alcohol abstinence, and strong perceived social support, were normalized. At the same time, the same three output variables were also normalized.

For both ANN–MLP models, the architecture was intentionally kept parsimonious because the analysis was based on a small cross-sectional sample of 27 EU Member States. Each model included one input layer, one hidden layer with a single hidden neuron, and one output layer with three dependent variables. A sigmoid activation function was used in both the hidden and output layers, and the sum of squares was used as the error function. This configuration was selected to detect potential nonlinear relationships while limiting the risk of overfitting. The cases were split into training and test sets in SPSS, and model performance was evaluated separately for each stage using the sum of squared errors and the average overall relative error. The convergence process followed the SPSS stopping rule, with one consecutive step and no decrease in error, and error computations based on the testing sample.

Given the limited number of observations, advanced validation procedures such as k-fold cross-validation or bootstrapping were not applied, because they would have further reduced the effective training sample and could have produced unstable estimates. Instead, robustness was addressed through three complementary strategies: maintaining a very simple ANN architecture, comparing training and test errors to identify potential overfitting, and interpreting the ANN results alongside the GLM findings. Therefore, the ANN–MLP models are used to identify possible nonlinear patterns and relative variable importance, not to claim strong predictive generalizability. This methodological choice is consistent with the study's exploratory and systemic purpose.

In the final stage, the analysis employed hierarchical cluster analysis to classify EU Member States into distinct health-performance typologies. The classification was based on the three health outcome indicators: healthy life years at birth, life expectancy at birth, and the share of people reporting good or very good perceived health. Squared Euclidean distance was used as the distance measure, while Ward's agglomerative method was applied to minimize within-cluster variance and obtain internally homogeneous groups [84,85].

The selection of the final number of clusters was based on several complementary criteria rather than on a single statistical rule. First, the dendrogram obtained from Ward's hierarchical procedure was inspected to identify the stage at which relatively large increases in the fusion distance indicated a meaningful separation among cases. Second, the interpretability of the resulting groups was assessed by comparing the final cluster centers for the three health outcome indicators. Third, the solution stability was examined through the iteration history and the absence of further changes in the cluster centers after convergence. Finally, the resulting classification was compared with descriptive differences in healthcare resources and positive health determinants to evaluate whether the clusters reflected coherent systemic profiles. Given the small number of observations, the cluster

analysis was used as an exploratory classification technique, and the resulting typologies should be interpreted as indicative groupings rather than definitive categories.

The distance between observations is calculated using the following formula:

$$d_{il}^2 = \sum_{m=1}^q (z_{im} - z_{lm})^2 \quad (4)$$

d_{il}^2 —the squared Euclidean distance between countries i and l ;

z_{im}, z_{lm} —the standardized values of clustering variable m for countries i and l ;

q —the number of clustering variables.

$$\Delta(A, B) = \frac{n_A n_B}{n_A + n_B} \| \bar{z}_A - \bar{z}_B \|^2 \quad (5)$$

$\Delta(A, B)$ —the increase in within-cluster variance caused by merging clusters A and B

n_A, n_B —the numbers of observations in the two clusters;

$\bar{z}_A, \bar{z}_B$ —the centroid vectors.

The resulting cluster solution was then interpreted using the dendrogram, final cluster centers, convergence history, and substantive differences among the identified groups.

Across all methodological stages, the notation was standardized using indices i for countries, j for input variables, k for output variables, and h for hidden neurons or latent dimensions, depending on the model. This approach ensures consistency across the factor analysis, GLM, ANN-MLP, and clustering procedures and improves the mathematical transparency of the empirical strategy.

By applying these methods within a unified analytical framework, the study offers a thorough view of the complexity of healthcare systems in the European Union. It establishes a robust methodological base for testing hypotheses and analyzing empirical findings.

4. Results

4.1. Results of the Factor Analysis

To evaluate Hypothesis H1, the study employed exploratory factor analysis using Principal Component Analysis (PCA) to determine how well the chosen healthcare system resource indicators group into a single latent construct. Before extracting factors, the analysis confirmed that the assumptions for dimensionality reduction were met, demonstrating that the data were suitable for this process.

The Kaiser–Meyer–Olkin (KMO) measure is 0.657, above the usual minimum threshold, suggesting that the correlations among variables are sufficiently consistent to support factor analysis. Additionally, Bartlett's test of sphericity is significant ($\chi^2 = 58.831$; $p < 0.001$), confirming that the correlation matrix differs from an identity matrix and that the variables exhibit meaningful intercorrelations.

The correlation analysis shows a link between current healthcare expenditure (CHE) and long-term care expenditure (LTE), indicating structural complementarity between these components of healthcare system financing. Correlations with the number of physicians (PN) seem more moderate, suggesting that human resources play a different role than financial aspects of the system.

The PCA results reveal a single principal component with an eigenvalue of 2.064, explaining about 68.8% of the total variance. This significant share of explained variance suggests a dominant underlying factor, which can be understood as healthcare system resources. Communality values highlight the contributions of healthcare and long-term

care expenditures to this factor, while the variable representing the number of physicians has a smaller but still meaningful contribution (see Table 2).

Table 2. Communalities and factor matrix for the healthcare system resources factor.

	Initial	Extraction	Factor 1
CHE	1.000	0.955	0.977
LTE	1.000	0.896	0.947
PN	1.000	0.213	0.462

Source: author's design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

High factor loadings for CHE and LTE indicate they are linked to the identified factor, underscoring the importance of financial factors and long-term care in determining healthcare system capacity. Even though the PN variable has a lower loading, it still exceeds the minimum threshold, indicating that the availability of medical personnel is a supplementary element of the system's resources.

Overall, these results support the validity of the latent construct "healthcare system resources," thereby confirming Hypothesis H1 and providing a solid foundation for its use in subsequent GLM and nonlinear analyses.

To evaluate the underlying structure of positive health determinants, the study used exploratory factor analysis PCA on six indicators of healthy behaviors and conditions at the population level. Before extracting components, the analysis confirmed that the data were suitable for this method, showing that its use was appropriate.

The Kaiser–Meyer–Olkin (KMO) measure is 0.677, reflecting adequate sampling suitability for factor analysis. Bartlett's test of sphericity is significant ($\chi^2 = 37.048$; $p = 0.001$), indicating that meaningful correlations exist among variables and supporting the use of dimensionality reduction. The correlation matrix reveals moderate positive relationships among key health-promoting behaviors such as physical activity, healthy eating, and non-smoking. Conversely, the frequency of alcohol consumption classified as "never" or "not in the last 12 months" shows negative correlations with other indicators, suggesting a distinct yet conceptually aligned dynamic within the set of health determinants.

The PCA results reveal a single principal component with an eigenvalue of 2.661, accounting for about 44.4% of the total variance. Although this explained variance is less than that of the healthcare resources factor, it remains acceptable for a behavioral and social construct that exhibits greater heterogeneity across the population. Communality analysis indicates consistent contributions from physical activity, non-smoking, and low alcohol consumption frequency, whereas perceived social support contributes very little, suggesting a weaker association within the identified factor structure (Table 3).

Table 3. Communalities and factor matrix for the positive health determinants factor.

	Initial	Extraction	Factor 1
BMIN	1.000	0.388	0.623
PAT	1.000	0.681	0.825
DCFV5	1.000	0.429	0.655
STPNS	1.000	0.549	0.741
FACN	1.000	0.588	−0.767
OPSSS	1.000	0.025	0.158

Source: author's design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The factor loadings indicate an association among physical activity, non-smoking, and healthy eating, suggesting that this factor primarily reflects a health-oriented behavioral profile. The negative loading of the FACN variable indicates an inverse relationship with

the other indicators, while remaining conceptually consistent, suggesting that alcohol abstinence is a complementary aspect of a healthy lifestyle. In contrast, perceived social support contributes only slightly to the factor, suggesting it may serve more as a separate contextual factor than as part of the core health-promoting behaviors.

Overall, these results somewhat support Hypothesis H1 concerning positive health determinants. They confirm a dominant latent construct but also emphasize the complexity and diversity of this domain, an inherent feature of healthcare systems viewed from a systemic perspective.

To assess the structural coherence of the indicators used to measure health outcomes, the study applied exploratory factor analysis using the Principal Component Analysis (PCA) method to three variables: healthy life years at birth (HLYB), life expectancy at birth (LEB), and the proportion of the population reporting good or very good perceived health (GVGPH). Preliminary analysis indicates that the data meet the necessary conditions for dimensionality reduction.

The Kaiser–Meyer–Olkin (KMO) measure is 0.694, exceeding the recommended minimum and indicating satisfactory sampling adequacy for factor analysis. Bartlett’s test of sphericity is statistically significant ($\chi^2 = 25.712$; $p < 0.001$), confirming substantial correlations among the variables. The correlation matrix shows moderate to positive associations among all three indicators, reflecting the interdependence between objective and subjective dimensions of health status.

The PCA results indicate the extraction of a single principal component with an eigenvalue of 2.188, explaining approximately 72.9% of the total variance in the data. This high proportion of explained variance confirms the presence of a robust latent construct that can be interpreted as population health outcomes. Communality values are high for all variables, indicating that the extracted factor adequately represents each indicator (Table 4).

Table 4. Communalities and factor matrix for the population health outcomes factor.

	Initial	Extraction	Factor 1
HLYB	1.000	0.694	0.833
LEB	1.000	0.699	0.836
GVGPH	1.000	0.795	0.892

Source: author’s design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The high and relatively balanced factor loadings indicate that all three indicators consistently contribute to defining the latent construct, capturing both the quantitative dimension of longevity and the qualitative dimension of perceived health status. This convergence between objective and subjective indicators strengthens the conceptual validity of the factor and supports its use as a synthetic dependent variable in subsequent analyses.

Overall, the results of the factor analyses of healthcare system resources, positive health determinants, and health outcomes confirm Hypothesis H1 by demonstrating distinct, coherent, and analytically relevant latent constructs from a systemic perspective on health in the European Union.

4.2. Univariate General Linear Model (GLM)

To test Hypothesis H2, the study estimated a univariate Generalized Linear Model (GLM) with the synthetic factor of health outcomes as the dependent variable. In contrast, the factors corresponding to healthcare system resources and positive health determinants entered the model as independent variables. The use of previously extracted factor scores enables an integrated analysis of relationships among the identified subsystems, reduces the risk of multicollinearity, and facilitates interpretation within a systems-thinking framework.

Descriptive analysis of the underlying variables indicates substantial variability across European Union member states in healthcare resources, health-promoting behaviors, and population health outcomes. Measures of skewness and kurtosis generally fall within acceptable ranges, which suggests that the core assumptions of the linear model are reasonably satisfied for the analyzed data.

The GLM results indicate that the estimated model is statistically significant overall ($F = 6.860$; $p = 0.004$) and explain approximately 36.4% of the variance in the health outcomes factor ($R^2 = 0.364$; adjusted $R^2 = 0.311$). This result indicates a statistically relevant association between the explanatory factors and health performance at the Member State level, without implying causal influence (Table 5).

Table 5. Tests of between-subject effects for the healthcare system resources factor.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
Corrected Model	9.457	2	4.728	6.860	0.004	0.364	13.719	0.885
Intercept	0.000	1	0.000	0.000	1.000	0.000	0.000	0.050
HR	5.188	1	5.188	7.526	0.011	0.239	7.526	0.749
PHD	0.239	1	0.239	0.347	0.561	0.014	0.347	0.087
Error	16.543	24	0.689					
Total	26.000	27						
Corrected Total	26.000	26						

Source: author's design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

The analysis of individual associations shows that healthcare system resources are positively and significantly associated with health outcomes ($p = 0.011$), with a moderate effect size (partial $\eta^2 = 0.239$). This indicates that Member States with higher levels of financial and human healthcare resources tend to report better outcomes in life expectancy, healthy life years, and self-rated health.

In contrast, positive health determinants, when combined as a single synthetic factor, are not statistically significantly associated with the health outcomes factor in this linear model ($p = 0.561$), and their effect size is minimal. This indicates that the relationship between health-promoting behaviors and population outcomes is not fully represented by a straightforward linear specification, especially when analyzed alongside healthcare system resources (see Table 6).

Table 6. Parameter Estimates for GLM.

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared	Noncent. Parameter	Observed Power
					Lower Bound	Upper Bound			
Intercept	−0.0000000001063	0.160	0.000	1.000	−0.330	0.330	0.000	0.000	0.050
HR	0.715	0.261	2.743	0.011	0.177	1.254	0.239	2.743	0.749
PHD	−0.0154	0.261	−0.589	0.561	−0.692	0.385	0.014	0.589	0.087

Source: author's design with SPSS v.27.0 (IBM Corporation, Armonk, NY, USA).

Parameter estimates indicate a positive, statistically significant cross-sectional association between healthcare resources and health outcomes. In contrast, the coefficient for positive health determinants is negative but statistically insignificant, with its confidence

interval including zero. This suggests that, within this analytical framework, the model does not identify a linear effect for these determinants.

Overall, the GLM results provide partial support for Hypothesis H2. Although healthcare system resources are positively and significantly associated with health outcomes, positive health determinants do not show a significant linear association in this model. This finding underscores the need to explore more complex, nonlinear relationships between positive health determinants and health status, an issue addressed in the following section using artificial neural networks, consistent with the systemic perspective adopted in this study.

4.3. Artificial Neural Network-Based Models (ANN–MLP)

To explore potential nonlinear links between healthcare resources and health outcomes, the study employed a Multilayer Perceptron (ANN–MLP) neural network. This method was chosen to explore possible nonlinear associations between institutional indicators and population-level health outcomes, and to build on GLM results that demonstrated the limitations of a purely linear approach.

The ANN model incorporates three input variables representing healthcare system resources: current healthcare expenditure (CHE), long-term care expenditure (LTE), and the number of physicians (PN). It predicts three health outcome indicators: healthy life years at birth (HLYB), life expectancy at birth (LEB), and self-perceived health status (GVGPH). The network features a single hidden layer with a single neuron and a sigmoid activation function, enabling an exploratory examination of potential nonlinear patterns while mitigating overfitting risks associated with the small dataset (see Figure 1).

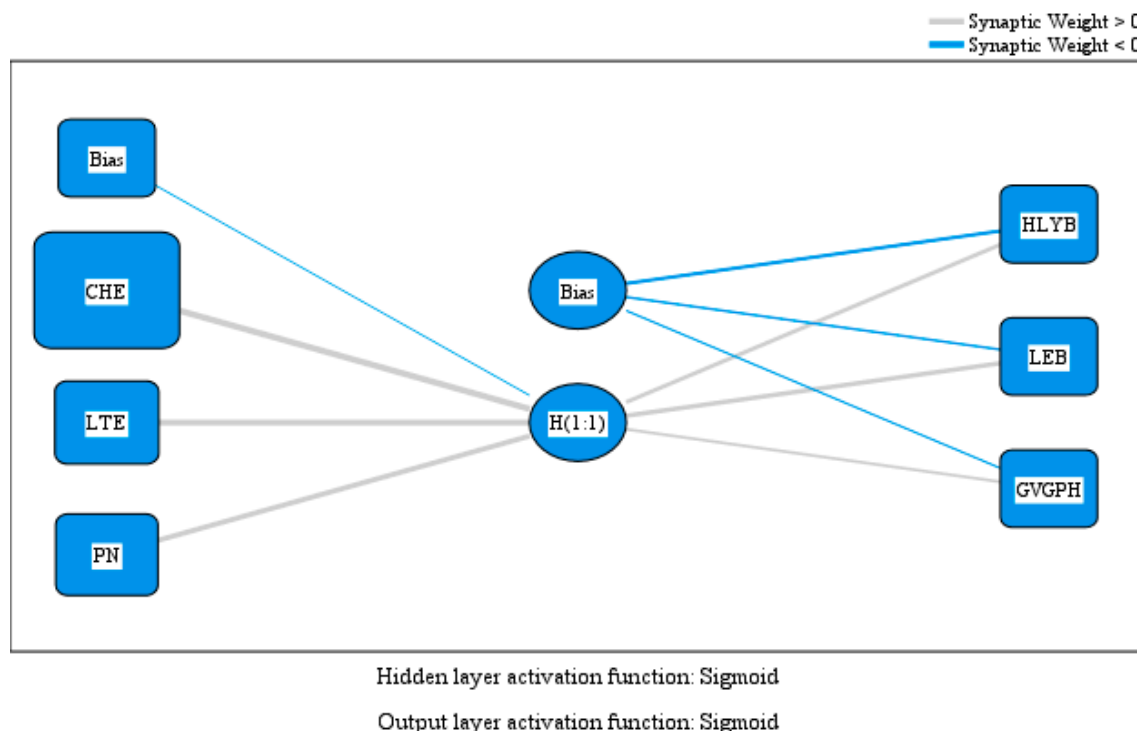


Figure 1. ANN–MLP model illustrating the systemic relationships between institutional inputs and population health outcomes. Source: authors’ design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Given the relatively small sample size (27 EU Member States), the ANN architecture was deliberately simplified to a single hidden layer with one neuron to reduce the risk of

overfitting and ensure model stability. The ANN is used primarily as an exploratory tool to detect potential nonlinear patterns rather than for predictive generalization.

The model performance suggests acceptable exploratory stability within the limits of the small sample. The mean relative error at the test stage is 0.520, lower than the corresponding value during training, suggesting no overfitting and acceptable stability of the estimates. Differences across dependent variables indicate that life expectancy is predicted with higher accuracy than healthy life years and self-perceived health, likely reflecting its more structural and less volatile nature.

The sum of squared errors equals 0.367 during the training phase and 0.238 during the testing phase. Table 7 reports the predicted values, together with the absolute and normalized importance of the input variables.

Table 7. Parameter estimates from the ANN–MLP model that capture systemic relationships between institutional inputs and population health outcomes.

Predictor		Predicted				Importance	Normalized Importance
		Hidden Layer 1	Output Layer				
			H(1:1)	HLYB	LEB		
Input Layer	(Bias)	−0.032					
	CHE	10.738				0.470	100.0%
	LTE	7.129				0.269	57.2%
	PN	6.102				0.261	55.4%
Hidden Layer 1	(Bias)		−1.023	−0.491	−0.202		
	H(1:1)		1.318	2.048	0.872		

Source: authors' construction using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Due to the limited sample size, advanced validation techniques such as cross-validation or bootstrapping were not used, as they would further reduce the effective training sample size. Therefore, the ANN results should be interpreted as exploratory, aimed at identifying potential nonlinear patterns rather than providing a predictive model.

The parameter estimates describe the internal structure of the ANN–MLP model and indicate how the input variables contribute to the modelled nonlinear association between healthcare resources and population health outcomes. The connection weights from the input to the hidden layers indicate that all three healthcare resource variables contribute to the ANN model, suggesting their combined influence on systemic performance. Notably, current healthcare expenditure (CHE) has the highest connection weight to the hidden neuron (10.738), suggesting its dominant role within the model structure. The importance analysis further supports this, with CHE having the highest normalized importance (100%), followed by long-term care expenditure (LTE) at 57.2% and the availability of medical personnel (PN) at 55.4%.

At the output layer, the coefficients connecting the hidden neuron to the dependent variables highlight differences in how health outcomes are modelled in relation to nonlinear combinations of system resources. The higher value for life expectancy at birth (LEB = 2.048) indicates it is most sensitive to intricate interactions among institutional resources, followed by healthy life years at birth (HLYB = 1.318) and self-perceived health status (GVGPH = 0.872). These findings suggest that, within the ANN model, objective outcomes appear more closely associated with nonlinear resource configurations than subjective indicators, which are more influenced by contextual and cultural factors.

Overall, the ANN results suggest the possible presence of nonlinear patterns between healthcare system resources and population health outcomes. However, given the limited number of observations and the absence of advanced validation procedures, these findings should be interpreted as exploratory rather than confirmatory. They provide indicative support for Hypothesis H3 by showing that the relationships among variables may involve nonlinear configurations that the GLM does not fully capture. Therefore, the ANN–MLP results should be understood as a complementary analytical perspective rather than definitive evidence of nonlinear mechanisms.

To further investigate the nonlinear links between positive health factors and outcomes, the study employs a second Multilayer Perceptron (ANN–MLP) neural network. This model considers six key variables related to health-promoting behaviors and conditions at the population level: maintaining a normal body mass index (BMIN), participating in physical activity (PAT), consuming enough fruits and vegetables daily (DCFV5), not smoking (STPNS), abstaining from alcohol (FACN), and having perceived social support (OPSSS). The three health outcome components, HLYB, LEB, and GVGPH, remain the dependent variables (see Figure 2).

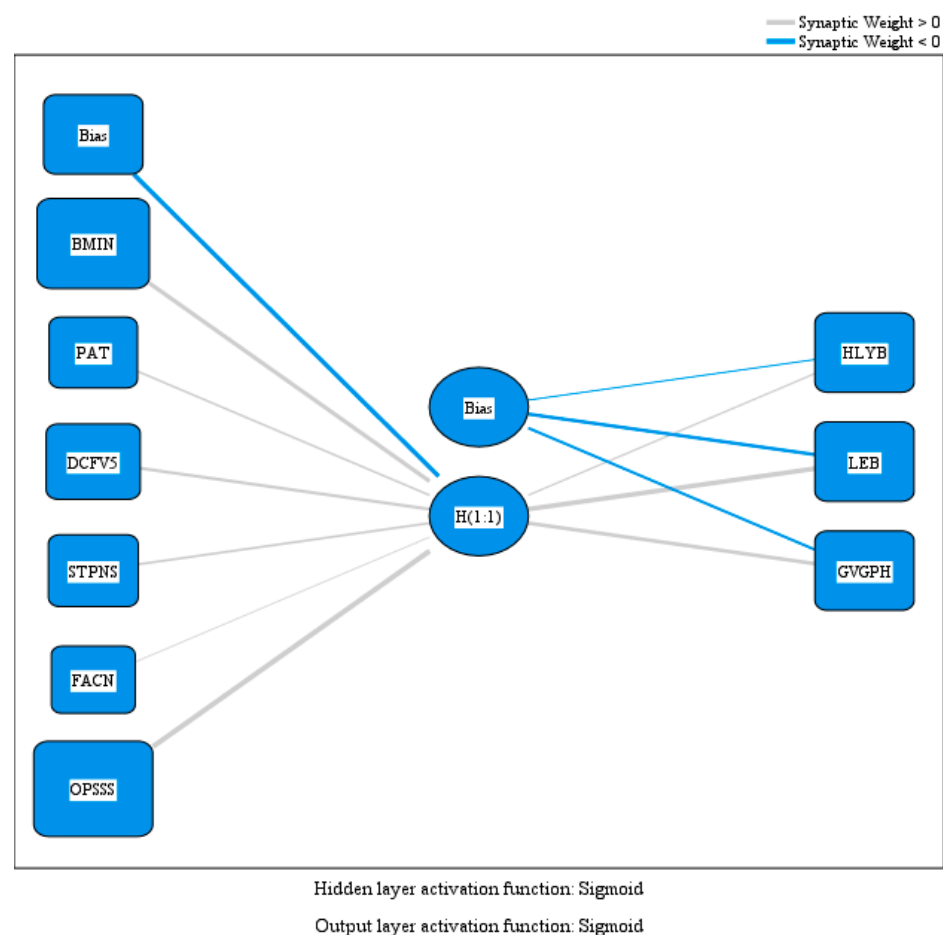


Figure 2. ANN–MLP model illustrating the systemic relationships between positive health determinants and health outcomes. Source: authors' design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The network architecture is comparable to that of the previous model and includes a single hidden layer with a single neuron and sigmoid activation. This structure allows an exploratory examination of possible nonlinear associations among positive health determinants while avoiding overparameterization, given the relatively small sample size. Model performance indicates moderate exploratory performance, with a mean relative error of

0.675 on the test sample. Although this error level is higher than that observed in the health-care resources-based model, it reflects the more heterogeneous and context-dependent nature of behavioral and social determinants.

Differences across dependent variables are noteworthy. Life expectancy at birth is predicted with relatively higher accuracy. In contrast, self-perceived health status shows greater variability in error, suggesting heightened sensitivity to contextual factors that aggregated indicators capture less effectively. This observation aligns with the existing literature, which emphasizes the subjective and culturally embedded nature of health perception (Table 8).

Table 8. Parameter estimates in the ANN–MLP model capturing systemic relationships between positive health determinants and health outcomes.

Predictor		Predicted				Importance	Normalized Importance
		Hidden Layer 1	Output Layer				
			H(1:1)	HLYB	LEB		
Input Layer	(Bias)	−3.193					
	BMIN	2.416				0.297	83.4%
	PAT	0.683				0.081	22.8%
	DCFV5	1.157				0.132	37.2%
	STPNS	0.789				0.094	26.3%
	FACN	0.362				0.041	11.5%
	OPSSS	3.497				0.356	100.0%
Hidden Layer 1	(Bias)		−0.528	−1.776	−0.975		
	H(1:1)		0.634	3.405	2.004		

Source: authors' construction using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The parameter estimates in Table 8 provide a detailed view of the nonlinear associations modelled between positive health determinants and health outcomes, highlighting their distinct roles within the ANN–MLP model's architecture. The connection weights between the input layer and the hidden neuron show an uneven distribution of contributions across the determinants analyzed, suggesting the presence of factors that play a central role in shaping population health performance. In this regard, perceived social support (OPSSS) has the highest connection weight to the hidden layer (3.497), suggesting a dominant contribution to the ANN's nonlinear aggregation mechanism. The relative importance analysis reinforces this finding, showing that OPSSS has the highest normalized importance (100%) and positions this social dimension as a pivotal element of the model.

In addition to social support, maintaining a healthy body mass index (BMI) plays a major role at the input layer, with a connection weight of 2.416 and an importance score of 83.4%. Proper intake of fruits and vegetables (DCFV5) has intermediate significance, with a normalized importance of 37.2%, while physical activity (PAT) and non-smoking status (STPNS) have a more moderate impact. The lack of alcohol consumption (FACN) has the lowest importance at 11.5%, indicating a supplementary role within the nonlinear arrangement of positive health factors.

At the output layer, the coefficients linking the hidden neuron to the dependent variables reveal significant differences in the sensitivity of health outcomes to nonlinear combinations of positive health determinants. The highest value, life expectancy at birth (LEB = 3.405), suggests that this indicator is most strongly associated with positive health

determinants in the modelled nonlinear association, followed by self-perceived health status (GVGPH = 2.004) and healthy life years at birth (HLYB = 0.634). These results suggest that the associations between positive health determinants and health outcomes may not be uniform or strictly additive; rather, they depend on systemic thresholds and specific combinations of key factors, particularly those with social and behavioral characteristics.

Overall, the results of the second ANN–MLP model provide additional exploratory support for Hypothesis H3. They suggest that the relationships between positive health determinants and population health outcomes may include nonlinear components, especially when behavioral and social variables are considered jointly. Nevertheless, these results should be interpreted with caution, as the limited sample size does not allow for strong predictive validation or definitive confirmation of nonlinear mechanisms. The ANN–MLP model should therefore be viewed as an exploratory tool for detecting possible patterns rather than as a confirmatory model.

Taken together, the two ANN–MLP models do not provide strict statistical confirmation of nonlinear mechanisms, but they offer exploratory evidence that the relationships among healthcare resources, positive health determinants, and population health outcomes may involve nonlinear configurations. Therefore, Hypothesis H3 is not considered definitively validated but rather partially and exploratorily supported. This interpretation is consistent with the limited sample size, the cross-sectional design, and the role of ANN–MLP models as complementary tools for identifying possible systemic patterns.

4.4. Cluster Analysis of Health Outcome Indicators

To identify distinct typologies of European Union Member States based on health performance, the study applied cluster analysis using squared Euclidean distance and Ward's linkage method, with health outcome indicators, healthy life years at birth (HLYB), life expectancy at birth (LEB), and the proportion of the population reporting good or very good health (GVGPH), as classification variables. This approach enables the identification of emergent patterns of health performance resulting from the complex interplay among system resources, positive health determinants, and institutional and socio-cultural contexts.

The results indicate a two-cluster solution, selected through joint interpretation of the dendrogram, the final cluster centers, and the classification process's stability. The dendrogram suggested that the main separation among Member States occurs at the level of two broad groups, while more detailed subdivisions mainly reflect internal heterogeneity within the better-performing group rather than clearly distinct health-performance regimes. The algorithm converged after two iterations, with no further changes in the cluster centers, which indicates a stable classification structure within the limits of the small sample. Therefore, the two-cluster solution was retained because it offered the most parsimonious and substantively interpretable distinction between Member States with higher and lower population health outcomes (Figure 3).

This stability suggests a clear separation among Member States based on the analyzed health profiles. The final cluster centers reveal substantial differences between the two groups. As an additional validation-oriented check, the two-cluster solution was examined through the final cluster centers and descriptive between-cluster comparisons. The final centers show a coherent separation across all three health outcome indicators: Cluster 1 records higher values for healthy life years at birth, life expectancy, and self-perceived good or very good health, whereas Cluster 2 records lower values on the same indicators. Descriptive ANOVA results also indicate sizeable differences between the two groups for HLYB, LEB, and GVGPH. However, these statistics are interpreted only as descriptive evidence of separation, not as formal hypothesis tests, because the clustering procedure

itself maximizes between-group differences. This cautious interpretation strengthens the methodological transparency of the analysis while avoiding overstatement of the cluster validation.

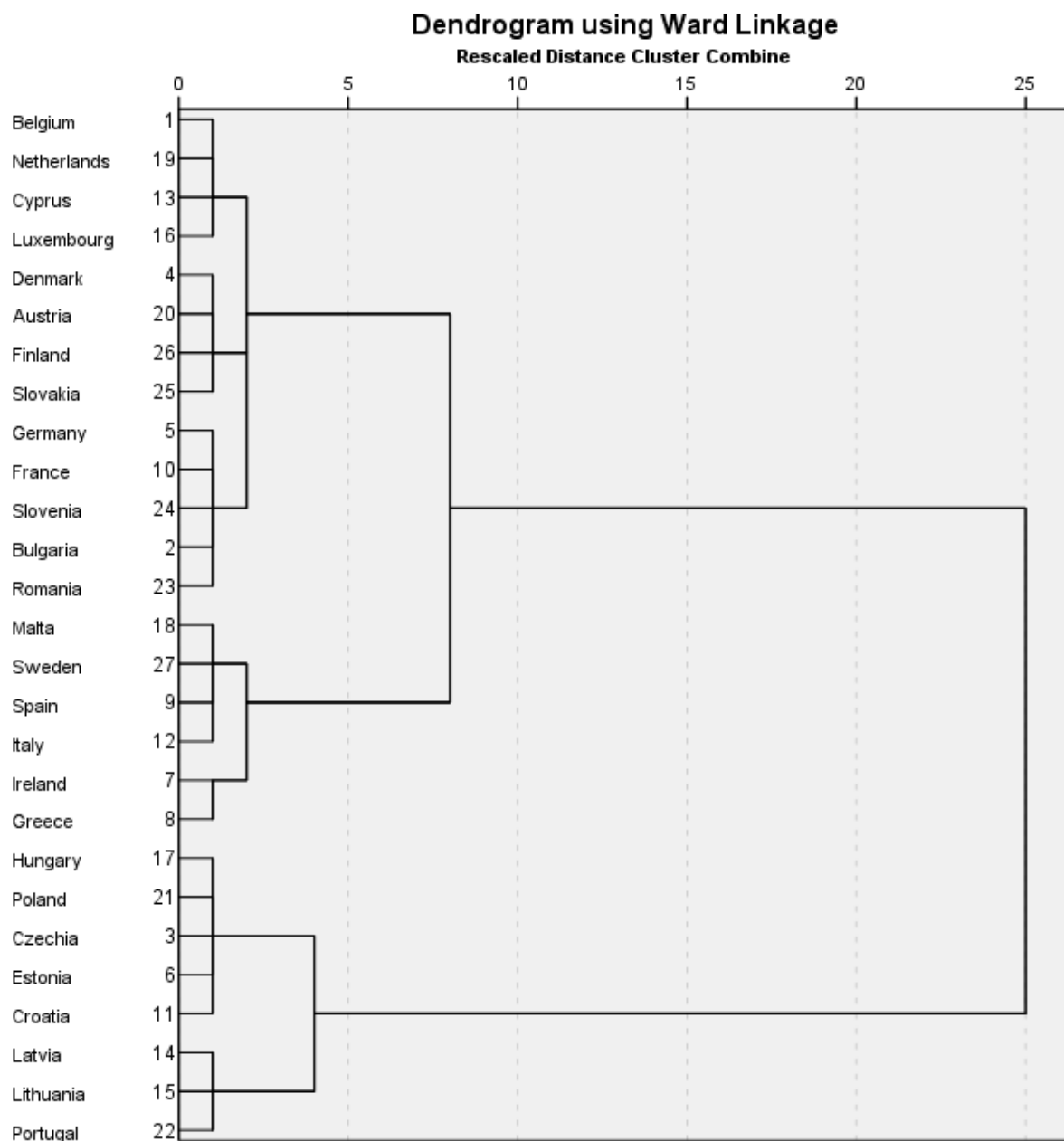


Figure 3. Dendrogram. Source: authors' design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Cluster 1 shows higher values across all three health outcome indicators (HLYB ≈ 64.4 years, LEB ≈ 81.7 years, and GVGPH $\approx 72.6\%$), suggesting a more favorable population health profile. By contrast, Cluster 2 shows lower values (HLYB ≈ 58.4 years, LEB ≈ 78.1 years, and GVGPH $\approx 56.2\%$), indicating a more vulnerable health profile.

A detailed analysis of the mean values across two clusters reveals distinct structural differences among European Union Member States in their healthcare resources, positive health determinants, and population health outcomes (see Table A1 in the Appendix A). Cluster 1, which includes countries with better health performance, has an average health-care expenditure of around 2949 PPS per capita, notably higher than the EU average of

2600 PPS. This discrepancy aligns with increased long-term care spending and greater availability of medical personnel, with an average of over 77,000 physicians, compared with roughly 36,900 in Cluster 2.

In parallel, the profile of positive health determinants shows a more favorable configuration in Cluster 1, where the proportion of the population with a normal body mass index is around 45% and average physical activity levels exceed 54%, compared with less than 39% in Cluster 2. Differences also emerge in dietary behaviors, as states in Cluster 1 report higher consumption of fruits and vegetables and a larger share of non-smokers. By contrast, Cluster 2 shows higher rates of abstaining from alcohol, suggesting heterogeneous behavioral patterns that do not automatically translate into superior health outcomes.

These structural differences are reflected in distinct health outcome profiles. Cluster 1 reports average values of approximately 64 years for healthy life years at birth (HLYB), 81.4 years for life expectancy, and over 72% for self-perceived good or very good health. In contrast, Cluster 2 shows a consistent gap, with average values of approximately 58.6 years for HLYB, 78.1 years for life expectancy, and only 55% for self-perceived health. The disparity is particularly pronounced for subjective indicators, suggesting that health perceptions respond to institutional and social contexts more than to strictly demographic measures.

A more granular analysis at the subcluster level within Cluster 1 reveals meaningful internal stratification. Subcluster 1.2, which includes Sweden, Ireland, Spain, and Italy, records the highest values across all three health outcome indicators, with averages exceeding 70 years for HLYB and 83 years for life expectancy. These states combine high levels of financial resources with favorable profiles of positive health determinants, particularly diet, social support, and physical activity. Subcluster 1.1, while still exhibiting health performance, shows more moderate values for behavioral determinants, suggesting that higher institutional resource levels can partially compensate for less favorable lifestyle profiles.

By comparison, states in Cluster 2 exhibit lower resource availability and less favorable positive health determinants, which constrain healthcare systems' capacity to achieve robust population health outcomes. Although some countries in this cluster approach the European average on specific dimensions, the absence of a coherent configuration across resources, behaviors, and social contexts is associated with less favorable health outcome profiles.

From a systemic perspective, these findings suggest that health performance across the European Union is not uniformly distributed but can be described through exploratory typologies associated with specific configurations of institutional resources, health-promoting behaviors, and socioeconomic contexts. The identified clustering structure has important policy implications. Member States in the higher-performing cluster appear to combine stronger institutional resources with more favorable configurations of health determinants, suggesting that integrated strategies may be relevant for supporting better health outcomes. In contrast, countries in the lower-performing cluster exhibit structural gaps in both resources and behavioral determinants, indicating that isolated policy interventions may be insufficient. These findings support the need for differentiated policy approaches tailored to cluster-specific profiles rather than uniform strategies across the European Union. Moreover, the cluster typologies highlight the importance of aligning investments in healthcare systems with interventions targeting social and behavioral determinants to reduce structural health inequalities. However, the absence of external validation of the clusters suggests that these typologies should be interpreted as indicative groupings rather than definitive classifications.

The selection of the two-cluster solution was supported by the dendrogram structure, the algorithm's convergence, the final cluster centers, and the substantive interpretability of the resulting groups. Cluster 1 consistently shows higher values for healthy life years, life expectancy, and self-perceived health, whereas Cluster 2 shows a more vulnerable health profile. Nevertheless, the clustering results should be interpreted cautiously. The ANOVA statistics are used only as descriptive indicators of separation, not as inferential validation, and the absence of external validation means that the resulting typologies remain exploratory. Thus, the cluster analysis provides indicative support for Hypothesis H4 rather than definitive evidence of stable health-system categories.

5. Discussion

The results of this study provide exploratory empirical support for the value of a systems-thinking approach to analyzing healthcare systems in the European Union. They are consistent with the view that population health is associated with complex configurations of institutional resources, positive health determinants, and broader social contexts. This perspective aligns with the literature that conceptualizes healthcare systems as complex adaptive systems, in which relationships among components may involve interdependencies, feedback loops, and nonlinear dynamics [1,2,14].

Before interpreting the findings, it is important to distinguish between statistical association, systemic interaction, and causal explanation. The GLM results indicate cross-sectional associations among the analyzed latent constructs, particularly between healthcare system resources and population health outcomes. The ANN-MLP and cluster analyses offer exploratory insights into possible nonlinear configurations and heterogeneity among Member States. However, these patterns should not be interpreted as causally identified mechanisms. In this study, systemic interaction refers to the coexistence of institutional resources, behavioral determinants, and social conditions within national healthcare systems, rather than to causal interaction effects estimated through longitudinal or experimental designs. Therefore, the findings should be understood as evidence of associations and exploratory configurations that require further causal testing in future research.

The results related to Hypothesis H1 show that the selected indicators cluster into distinct, coherent latent constructs representing healthcare system resources, positive health determinants, and population health outcomes. This latent structure is consistent with observations from comparative European studies that isolated indicators cannot explain health performance and that a multidimensional analytical approach is required [5,49]. In particular, the coherence of the healthcare resources factor aligns with literature emphasizing the close interrelation among expenditure, human resources, and medical infrastructure within national systems [23,40]. By contrast, the more heterogeneous structure of positive health determinants reflects the complexity of health behaviors and social factors, consistent with the work of Solar and Irwin, who emphasize the contextual and intersectoral nature of health determinants. However, the relatively low explained variance of the positive health determinants factor (approximately 44.4%) indicates greater heterogeneity across behavioral and social variables. In addition, the weak loading on perceived social support suggests that this variable may capture a distinct dimension that is not fully aligned with the core behavioral construct. This result reflects the complex, multidimensional nature of health determinants, which may not be fully reducible to a single latent factor.

The results for Hypothesis H2 indicate a positive, statistically significant cross-sectional association between healthcare system resources and population health outcomes, corroborating findings from numerous econometric and public policy studies. The relationship between health expenditure and indicators such as life expectancy and healthy life years appears widely documented in OECD and European Union research [7,10,22]. The findings

of this study are consistent with the view that health investments and institutional capacity are closely linked to population health performance, even in contexts characterized by diminishing marginal returns, as endogenous growth models suggest [51].

This perspective also applies to the interpretation of subjective health indicators, such as self-perceived health. In more developed healthcare systems, higher expectations, greater medical awareness, and increased access to healthcare services may lead individuals to report lower perceived health, even when objective conditions are better. Conversely, populations in less developed contexts may report higher perceived health due to lower expectations. This paradox aligns with the theory of diminishing marginal returns and warrants caution when interpreting subjective health measures in cross-country comparisons.

In contrast, positive health determinants do not show a statistically significant linear effect in the GLM framework when analyzed alongside institutional resources. This aligns with other research indicating that the effects of health-related behaviors are often difficult to capture with aggregated linear models, especially at the national level [24,61]. The literature indicates that physical activity, healthy eating, and social support may be associated with health indirectly and cumulatively, a relationship that traditional linear methods often overlook [29,33]. Therefore, the absence of statistical significance in the GLM should not be viewed as evidence of no effect but rather as a limitation of the linear analytical approach.

This interpretation is further supported, in an exploratory sense, by the findings related to Hypothesis H3. The ANN-MLP models suggest the possible presence of nonlinear associations between positive health determinants and population health outcomes, but these patterns should not be interpreted as definitive evidence of nonlinear mechanisms. Given the limited number of country-level observations and the absence of advanced validation procedures, the ANN results should be understood as complementary exploratory insights that help identify potential configurations warranting further testing in larger or longitudinal datasets. The key contributions of perceived social support and maintaining a normal body mass index within the ANN framework align with the literature emphasizing the importance of social capital and relationships in reducing mortality and enhancing quality of life [31,62]. Additionally, these results are consistent with recent machine learning studies in population health, indicating that the impact of behavioral determinants varies with specific combinations of factors and threshold levels [4,67]. It is important to note that ANN-based results do not provide formal statistical inference, such as confidence intervals or hypothesis tests. Therefore, the identified nonlinear patterns should be interpreted cautiously as exploratory insights into potential system dynamics rather than definitive conclusions.

The results of the cluster analysis provide exploratory support for Hypothesis H4 and suggest indicative typologies of European Union Member States based on health outcomes. These typologies point to structural differences among European communities and are consistent with the literature documenting persistent health inequalities across regions and groups of countries [5,43]. However, the systemic approach adopted in this study adds an interpretive dimension by suggesting that these differences do not merely reflect variations in resource levels but rather emerge from complex configurations involving health behaviors. These findings should be interpreted as indicative, since no sensitivity analysis was conducted to assess the stability of the results under alternative specifications.

These findings also suggest that systemic heterogeneity among EU healthcare systems has direct policy relevance, as differences in health outcomes reflect not only variations in healthcare resources but also the ways institutional capacity interacts with behavioral and social determinants within specific governance contexts.

This research suggests that unidirectional health policies remain insufficient to reduce health disparities. In line with the conclusions advanced by [6,28], the sustainable transfor-

mation of healthcare systems requires integrated interventions that combine investments in institutional resources with strategies to strengthen communities and promote positive health determinants.

5.1. Theoretical Implications

The study's findings contribute to the healthcare systems literature, especially by enhancing the theoretical framework of systems thinking used to compare population health. The evidence that indicators form separate latent constructs supports the view that a single dominant dimension cannot explain health and that health should be seen as a multidimensional, emergent phenomenon. This outcome is consistent with theoretical claims that view healthcare systems as complex adaptive systems, in which institutional resources, individual behaviors, and social factors are interconnected and may shape one another over time. However, such dynamic relationships cannot be causally tested in the present cross-sectional design.

The study contributes to the understanding of how healthcare system resources relate to positive health determinants by showing that these elements do not function symmetrically or equally. It indicates that, in the linear model, institutional resources show a more direct statistical association with population health outcomes, whereas positive health determinants appear to be associated with health mainly through nonlinear, context-specific patterns. This distinction offers valuable nuance to the literature, which often views behavioral determinants either as minor factors or as replacements for institutional investment.

Using multiple methods together enhances analysis by going beyond basic descriptions. Factor analysis reveals hidden systemic patterns; GLM estimates average linear relations; ANN models explore possible nonlinear associations and threshold-like patterns; and cluster analysis uncovers emerging health system types. Collectively, these approaches provide a more complete view of the healthcare system's complexity, allowing analysis to move from examining isolated relationships to gaining integrated, system-wide insights.

5.2. Practical Implications

In practice, this study's findings inform public decision-makers and stakeholders engaged in health policy planning at the European and national levels. The observed association between healthcare system resources and population health underscores the need to sustain adequate funding and optimize the use of human resources and care services, especially given an aging population and rising prevalence of chronic diseases.

The findings also suggest that policies aimed solely at increasing institutional resources may be insufficient to optimize health performance. The influence of positive health factors, primarily identified using nonlinear models, suggests that interventions focused on lifestyle and social capital may be more relevant when policymakers integrate them into the healthcare system. However, the present findings do not estimate their causal effects. Key elements such as perceived social support, regular physical activity, and maintaining a healthy weight emerge as relevant contextual factors that may complement institutional investments, particularly within communities.

Cluster analysis offers a useful method for dividing states or regions by health performance, aiding the development of tailored, context-aware policies. Instead of applying a one-size-fits-all approach across Europe, the findings highlight the importance of adaptable strategies that consider each community's unique resource and determinant structures.

The systemic heterogeneity suggested by the cluster analysis has relevant policy implications. The differences between Member States should not be interpreted only as variations in healthcare expenditure, but as the result of interactions among institutional resources, behavioral and social determinants, and governance capacity. Higher-performing

systems appear to combine stronger financial and human resources with more favorable behavioral and social profiles. In contrast, lower-performing systems show more vulnerable configurations that are unlikely to be adequately addressed through isolated interventions. EU health policy should rely on differentiated strategies rather than uniform prescriptions. In countries with stronger healthcare resources, priorities should focus on efficiency, long-term care integration, prevention, and community-based health promotion. In countries with weaker health profiles, increased expenditure would likely be more effective if accompanied by reforms targeting access, institutional coordination, prevention, social support, and behavioral risk factors. These findings support a systemic policy approach in which healthcare investment, prevention policies, and social interventions are treated as complementary components of the same governance framework.

5.3. Limitations and Future Research Directions

Although this study makes valuable contributions, readers should be aware of certain limitations. The cross-sectional design limits understanding of how resources, determinants, and health outcomes evolve. It offers a clear snapshot of current configurations but does not support strong causal conclusions or long-term trend analysis.

For this reason, the empirical findings should be interpreted as cross-sectional associations rather than causal effects. The GLM identifies average statistical relationships among latent constructs, while the ANN–MLP and cluster analyses explore possible nonlinear patterns and systemic configurations. These methods can indicate whether variables coexist in meaningful empirical patterns, but they cannot determine the temporal ordering, direction of influence, or causal mechanisms linking institutional resources, behavioral determinants, social support, and population health outcomes.

Second, using nationally aggregated data can hide significant inequalities within regions or subpopulations. Positive health determinants, especially behavioral and social factors, can vary widely across Member States, and macro-level analysis may not capture these internal disparities. Moreover, certain indicators, such as self-perceived health and social support, are influenced by cultural contexts and differences in subjective reporting, potentially affecting cross-country comparisons.

In addition, self-perceived health indicators may introduce comparability biases across countries because perceptions of health are inherently relative and shaped by cultural, educational, and socioeconomic factors. In more developed contexts, individuals may report lower perceived health despite objectively better conditions, reflecting higher expectations and awareness. In contrast, populations in less developed settings may report comparatively higher perceived health. This potential paradox, consistent with diminishing marginal returns in perceived well-being, should be considered when interpreting cross-country differences.

Another limitation is the relatively small sample size, which may reduce the robustness of multivariate and machine-learning analyses. Although the ANN models were specified with a simplified architecture to mitigate overfitting, the results should be interpreted with caution, as they primarily capture indicative nonlinear relationships rather than fully generalizable patterns.

A further limitation concerns the interpretation of the ANN–MLP models. Although these models are useful for exploring potential nonlinear associations, the small sample of 27 EU Member States restricts their predictive and confirmatory value. The ANN architecture was intentionally simplified to reduce overfitting, and the results were interpreted together with the GLM findings. However, the absence of advanced validation procedures, such as k-fold cross-validation or bootstrapping, means that the ANN findings should be treated as exploratory indications of possible nonlinear patterns rather than as validated evidence.

of underlying mechanisms. Future research should test these relationships using larger datasets, longitudinal designs, and more robust machine-learning validation procedures.

Another limitation relates to the factor analysis results. Some extracted factors explain a moderate proportion of variance, particularly for positive health determinants, which may affect the robustness of the latent constructs. Furthermore, certain variables, such as perceived social support, exhibit weak loadings, suggesting that they may represent distinct dimensions not fully captured within the constructed factors.

The cluster analysis also has several limitations. Although the two-cluster solution was supported by dendrogram interpretation, convergence stability, final cluster centers, and descriptive between-cluster differences, it was not externally validated using independent datasets. In addition, the ANOVA results for the clusters were used only descriptively, as the clustering procedure was designed to maximize differences among cases. Therefore, the identified typologies should be interpreted as exploratory and indicative rather than definitive. Future studies could strengthen this classification by applying silhouette coefficients, alternative distance measures, k-means sensitivity checks, or longitudinal clustering procedures on larger datasets.

The cross-sectional design restricts causal inference. Although longitudinal analysis would provide deeper insights into dynamic relationships, the use of EHIS data constrains this possibility, as the survey is conducted in multi-year waves rather than annually. This limits the availability of consistent time-series data for all variables across EU Member States and prevents the construction of a robust longitudinal framework combining institutional and behavioral indicators.

Another limitation is the absence of robustness and sensitivity analyses, including tests of alternative model specifications or variable selection. As a result, the stability of the reported relationships cannot be fully assessed, and the findings should be interpreted with caution. Future research could address this issue by applying alternative specifications and testing the consistency of results across different model configurations.

Future research could extend the analysis within a longitudinal framework to examine dynamic relationships and the cumulative effects of health policies over time. Moreover, integrating regional- or individual-level data could provide a more granular understanding of the mechanisms through which positive health determinants influence population outcomes. From a methodological perspective, future studies may explore additional advanced nonlinear techniques or simulation approaches to deepen the understanding of healthcare system complexity.

6. Conclusions

This study offers a comprehensive analysis of healthcare systems in the European Union using a systems thinking approach, integrating traditional statistical methods with advanced nonlinear analysis. The results suggest that population health is associated with configurations of institutional resources, positive health determinants, and wider social factors. These relationships are complex and cannot be explained by simple or one-dimensional factors.

The study indicates that healthcare system resources are strongly associated with health performance in the analyzed cross-sectional dataset. Furthermore, health behaviors and social capital either strengthen or influence their effects. The exploratory evidence of possible nonlinear patterns and the indicative typologies of Member States highlight the relevance of tailored health policies that emphasize community involvement.

The study indicates that healthcare system resources are strongly associated with health performance in the analyzed cross-sectional dataset. For example, individuals in highly developed healthcare systems may report lower perceived health because of higher

expectations, greater health awareness, and increased medicalization, even when objective indicators are favorable. In contrast, individuals in less developed contexts may report higher perceived health despite poorer objective conditions, reflecting lower expectations and different cultural benchmarks. These contrasting patterns underscore the need to interpret subjective health indicators cautiously and in conjunction with objective measures.

The findings have important implications for public policy, as they show that EU healthcare systems require differentiated strategies tailored to their systemic profiles. Improving population health outcomes depends not only on increasing healthcare resources but also on strengthening the interactions among institutional capacity, behavioral determinants, social support, and governance mechanisms. Given the cross-sectional design, these findings should not be interpreted as evidence of causal effects. Their main contribution lies in identifying statistically relevant associations and exploratory systemic configurations that can guide future longitudinal, regional, or quasi-experimental research on the dynamics of EU healthcare systems.

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Abbreviations

The following abbreviations are used in this manuscript:

CHE	Current health care expenditure
LTE	Long-term care (health)
PN	Physicians
BMIN	Body mass index—normal
PAT	Performing health-enhancing physical activity (Aerobic, muscle-strengthening, or both)
DCFV5	Daily consumption of fruit and vegetables—5 portions or more
STPNS	Smoking of tobacco products—Non-smoker
FACN	Frequency of alcohol consumption—Never or not in the last 12 months
OPSSS	Overall perceived social support—Strong
HLYB	Healthy life years at birth
LEB	Life expectancy in absolute value at birth
GVGPH	Share of people with good or very good perceived health

Appendix A

Table A1. Cluster membership.

	CHE	LTE	PN	BMIN	PAT	DCFV5	STPNS	FACN	OPSSS	HLYB	LEB	GVGPH
Belgium	3868.81	898.07	36,343	48.0	39.1	15.1	80.6	23.2	34.6	62.4	82.1	74.1
Netherlands	3932.71	1096.24	65,121	48.9	81.6	29.5	78.9	22.2	32.8	61.0	82.2	74.8
Cyprus	1946.67	81.34	3768	47.7	32.3	7.9	74.5	29.0	66.7	62.5	82.4	77.0
Luxembourg	3741.24	708.12	1842	49.2	70.5	13.6	81.8	17.2	30.9	62.6	82.7	71.9
Denmark	3765.11	803.11	24,719	48.8	90.3	22.9	80.0	9.4	30.6	58.9	81.5	69.7
Austria	4004.44	572.94	46,987	46.3	73.0	5.6	73.8	20.1	55.5	57.3	82.0	71.3
Finland	3101.61	538.82	15,546	40.6	94.7	13.5	82.2	15.3	22.4	56.4	82.1	68.6
Slovakia	1519.29	5.9	19,454	40.0	43.4	8.5	72.4	28.4	24.2	56.2	77.8	65.2
Germany	4516.45	880.96	365,100	45.2	85.2	10.9	71.7	21.2	38.1	66.3	81.4	65.5
France	3678.26	578.14	213,180	50.3	43.5	19.5	76.0	23.0	38.1	64.1	82.9	66.7
Slovenia	2286.72	233.42	6812	41.8	58.3	5.3	76.8	26.4	37.1	60.9	81.6	66.7
Bulgaria	1334.06	1.63	29,549	44.1	19.6	5.0	63.8	29.7	26.2	66.3	75.2	67.2
Romania	1311.35	72.75	61,731	42.5	9.9	2.4	72.7	30.5	17.3	60.2	75.7	71.2
Subcluster 1.1 mean	3000.52	497.80	68,473.23	45.65	57.03	12.28	75.78	22.74	34.96	61.16	80.71	69.99
Malta	2958.13	556.6	2029	34.2	26.1	11.6	74.9	32.2	36.1	73.2	82.9	74.2
Sweden	3855.18	1048.38	44,075	48.0	95.4	7.6	87.4	19.1	32.2	73.3	83.2	76.0
Spain	2544.05	274.48	207,565	45.3	53.1	10.9	77.9	33.4	65.0	69.9	83.9	75.3
Italy	2528.03	269.09	241,945	51.4	31.2	10.5	77.6	34.8	31.7	68.3	83.6	72.9
Ireland	3481.8	754.01	16,366	43.7	57.2	32.9	81.8	22.6	57.8	69.6	82.8	84.3
Greece	1652.36	26.64	66,058	42.3	30.0	12.4	71.4	28.5	21.1	66.0	81.7	79.3
Subcluster 1.2 mean	2836.59	488.20	96,339.67	44.15	48.83	14.32	78.50	28.43	40.65	70.05	83.00	77.00
Cluster 1 mean	2948.75	494.77	77,273.16	45.17	54.44	12.93	76.64	24.54	36.76	63.97	81.43	72.21
Hungary	1494.64	59.21	34,137	38.9	55.1	8.2	72.8	29.1	38.4	61.7	76.4	58.5
Poland	1591.87	106.99	125,349	40.6	28.7	8.6	77.4	25.9	33.5	62.5	78.0	59.9
Czechia	2323.58	310.15	43,399	40.0	37.5	7.7	73.6	15.2	37.3	62.0	79.3	62.0
Estonia	1739.71	163.46	4603	42.4	43.4	13.3	75.2	22.8	16.8	55.8	78.8	56.6
Croatia	1429.75	44.79	14,312	34.5	35.1	9.8	74.3	38.3	45.0	57.4	78.6	60.5
Latvia	1436.48	71.6	6253	40.7	37.9	7.2	73.2	27.3	19.0	53.1	75.5	47.1
Lithuania	1898.63	142.8	12,768	42.7	41.3	15.9	76.3	28.6	26.8	57.5	76.4	46.2
Portugal	2268.82	108.34	54,744	43.4	28.8	14.4	83.0	30.0	31.8	59.2	81.8	50.1
Cluster 2 mean	1772.94	125.92	36,945.63	40.40	38.48	10.64	75.73	27.15	31.08	58.65	78.08	55.11
Eu mean	2600.36	385.48	65,324.26	43.76	49.71	12.25	76.37	25.31	35.07	62.39	80.44	67.14

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