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Analysis of structural health gaps in OECD countries using the Gowlad Index: A proposal for logarithmic weighted aggregation based on fuzzy logic

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Resumen.

El estudio evalúa las disparidades estructurales en el desempeño de los sistemas de salud de los países de la OCDE mediante un modelo de agregación logarítmica basado en lógica difusa. La investigación justifica su relevancia en la necesidad de medir inequidades que los enfoques tradicionales no logran capturar. Metodológicamente, se aplica el índice GOWLAD*, que integra ponderaciones redistributivas y funciones de distancia logarítmica para estimar el grado de rezago estructural entre países durante el periodo 2000–2021. Los resultados revelan una creciente divergencia en el desempeño sanitario y evidencian que las brechas no se deben al avance de los países líderes, sino a la lentitud en la mejora de los rezagados. El modelo propuesto constituye una herramienta innovadora y replicable que contribuye a la formulación de políticas públicas orientadas a la equidad, la eficiencia y la resiliencia de los sistemas de salud.

Palabras Clave: agregación logarítmica, desempeño del sistema de salud, lógica difusa, OCDE, política sanitaria.

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Abstract.

This study evaluates structural disparities in the health system performance of OECD countries using a logarithmic aggregation model based on fuzzy logic. Its relevance lies in addressing inequities that traditional efficiency approaches fail to capture. Methodologically, the research applies the GOWLAD* index, which integrates redistributive weighting and logarithmic distance functions to estimate structural lag across countries between 2000 and 2021. Results indicate a growing divergence in health performance, showing that disparities arise not from leading countries' progress but from slower improvement among lagging ones. The proposed model offers an innovative and replicable tool that supports public policy design aimed at promoting equity, efficiency, and resilience in health systems.

Keywords: logarithmic aggregation, health system performance, fuzzy logic, OECD, health policy.

Código JEL: I10, I18, C61, C63, O57

Introduction

Health is a fundamental human right and an essential pillar for sustainable social and economic development (United Nations, 2015; WHO, 2010). Despite progress achieved over recent decades and international commitments to achieve Universal Health Coverage (UHC), significant inequalities persist in access, quality, and health outcomes, particularly in low- and middle-income countries (Boerma et al., 2014; Hogan et al., 2018; MacKenbach & McKee, 2013). These structural gaps reflect not only limitations in financing and the availability of human resources, but also organizational weaknesses and systemic inequities that perpetuate cycles of exclusion (Kruk et al., 2018). In this context, the need for comprehensive and comparative tools to measure health system performance is increasingly recognized, as such tools can facilitate the formulation of more equitable and effective public policies (Moreno-Serra & Smith, 2012; Ng et al., 2014).

To address these inequalities in a structured manner, it is essential to employ comprehensive conceptual frameworks capable of examining the functional components of health systems. Among these, the functional building blocks framework proposed by the World Health Organization (WHO) has become a global reference, encompassing dimensions such as human resources, service delivery, access to medicines and technologies, financing, health information, and governance (Manyazewal, 2017; WHO, 2007).

In this study, three core blocks were selected: Human Resources, Medicines and Technology, and Financing, due to limited availability of comparable data for the Information and Governance blocks, as well as for certain service delivery indicators, a transversal block based on the UHC index was incorporated. This global index integrates indicators related to immunization, prenatal care, and avoidable hospitalization, serving as a synthetic complementary measure to capture access and effective coverage (Boerma et al., 2014; Hogan et al., 2018; Wagstaff & Neelsen, 2020).

Health is a fundamental human right and an essential pillar for sustainable social and economic development (United Nations, 2015; WHO, 2010). Despite progress achieved over recent decades and international commitments to achieve UHC, significant inequalities persist in access, quality, and health outcomes, particularly in low- and middle-income countries (Boerma et al., 2014; Hogan et al., 2018; MacKenbach & McKee, 2013). These structural gaps reflect not only limitations in financing and the availability of human resources, but also organizational weaknesses and systemic inequities that perpetuate cycles of exclusion (Kruk et al., 2018). In this context, the need for comprehensive and comparative tools to measure health system performance is increasingly recognized, as such tools can facilitate the formulation of more equitable and effective public policies (Moreno-Serra & Smith, 2012; Ng et al., 2014).

Once the conceptual blocks are defined, it is crucial to specify the indicators selected for each one. The choice of indicators should be grounded in robust empirical evidence and internationally recognized standards (Boerma et al., 2014; OECD, 2023b). In this study, the Human Resources block considers the density of physicians per 10,000 inhabitants, a key measure of care capacity (Campbell et al., 2013; Kassebaum et al., 2016; Scheffler & Arnold, 2019). The Medicines and Technology block includes the availability of hospital beds and CT scanners, reflecting diagnostic and hospital response capacity (OECD, 2023a). The Financing block comprises out-of-pocket expenditure, per capita health spending, and health expenditure as a percentage of GDP, variables associated with financial protection and governmental commitment (Moreno-Serra & Smith, 2012; Wagstaff et al., 2016; Xu et al., 2003). Finally, the transversal UHC block is based on a composite index summarizing coverage of essential services such as immunization (DTP3), prenatal care, and avoidable hospitalizations, serving as a key reference for assessing effective and equitable access (Boerma et al., 2014; Hogan et al., 2018; Wagstaff & Neelsen, 2020).

Despite the conceptual relevance and robustness of these indicators, various studies underscore the need for methodologies capable of integrating multiple dimensions and more accurately capturing relative gaps with respect to an optimal standard (Kruk et al., 2018; Ng et al., 2014; O'Donnell et al., 2008). Traditional indices often focus on absolute values or fixed thresholds, limiting their capacity to prioritize interventions and reduce structural inequalities (Anand & Hanson, 1997; Salomon et al., 2012). These limitations highlight the importance of adopting more sensitive and flexible approaches that enable better prioritization of actions and more precise and efficient resource allocation.

The objective of this study is to evaluate the health system performance of OECD member countries through the application of a fuzzy logic–based weighted logarithmic aggregation model. For this purpose, the GOWLAD* index is developed, a methodological variant that incorporates empirical optimal values by year and by variable, allowing the identification of patterns of relative lag and potential trajectories of structural convergence or divergence over selected years in the 2000–2021 period. This analysis provides a comparative metric of health system performance that captures relative lag trajectories and allows examination of structural inequalities across highly heterogeneous national contexts. The underlying hypothesis is that structural disparities among OECD health systems persist despite convergence efforts.

1. Background.

Health has long been recognized not only as a fundamental human right but also as an essential component of human and social development (United Nations, 2015; WHO, 2010). From the capability's perspective, Sen (1999) argues that health is both an intrinsic end and an instrumental means to expand individuals' real freedoms, enabling full participation in economic and social life. This ethical vision reinforces the need for equitable and efficient health systems that ensure effective access to essential services and mitigate persistent inequalities (Moreno-Serra & Smith, 2012).

Building on this approach, the World Health Organization (WHO, 2007) proposed a conceptual framework based on functional building blocks to analyze health systems comprehensively. This scheme acknowledges that health system performance depends not only on infrastructure or financing but also on the complex interaction between human resources, technology, financing, and effective service coverage (Manyazewal, 2017; OECD, 2023b). Recent literature has emphasized that the mere existence of infrastructure or financing does not guarantee equitable outcomes unless accompanied by strategies that strengthen problem-solving capacity and accessibility (Atun et al., 2015; Moreno-Serra & Smith, 2015).

Traditional aggregation methods, such as arithmetic or geometric means, have shown limitations when integrating multiple dimensions and capturing relative inequalities within health systems (Anand & Hanson, 1997; Salomon et al., 2012). These methodological limitations highlight the need for more flexible and sensitive analytical frameworks capable of reflecting structural inequities and supporting evidence-based decision-making in health policy.

2. Literature review.

The evaluation of health system performance has evolved from single-dimensional indicators toward multidimensional frameworks capable of integrating access, efficiency, and equity dimensions. A large body of research emphasizes that health outcomes are not solely determined by spending levels but by the structural configuration and coordination of system components (Atun et al., 2015; Moreno-Serra & Smith, 2012). Within this context, the World Health Organization's building blocks framework provides a comprehensive approach to assess system capacity and performance, highlighting the interdependence between human resources, infrastructure, financing, and governance (Manyazewal, 2017; WHO, 2007).

Empirical evidence demonstrates that the availability of human resources, particularly the density of physicians per 10,000 inhabitants, is a critical determinant of system responsiveness and population health outcomes (Campbell et al., 2013; Kassebaum et al., 2016; Scheffler & Arnold, 2019). Similarly, technological and infrastructural capacity, measured through the number of hospital beds per 1,000 inhabitants and CT scanners per million inhabitants, remains essential for ensuring timely and effective care (Atun et al., 2015; OECD, 2023a). These indicators collectively capture the structural dimension of health systems and their ability to deliver essential services efficiently.

Financial protection and investment are equally decisive. Out-of-pocket expenditure (OOP_Exp) continues to be one of the most sensitive indicators of health equity, as high household costs are directly linked to catastrophic spending and exclusion from care (Wagstaff et al., 2016; Xu et al., 2003). Complementarily, per capita expenditure and health spending as a share of GDP (Exp_per_cap and Exp_GDP) reflect the degree of public commitment to the right to health and the institutional priority assigned to healthcare financing (OECD, 2023c; WHO, 2010). Despite improvements in many OECD countries, persistent inequalities highlight that financial investment alone does not guarantee equitable outcomes (Ng et al., 2014).

In addition to these structural indicators, the UHC serves as an integrative measure of access and effective coverage. It combines preventive and curative service tracers, such as immunization (DTP3), antenatal care, and avoidable hospitalizations, into a synthetic index widely used for international comparison (Boerma et al., 2014; Hogan et al., 2018; Wagstaff & Neelsen, 2020) However, this composite indicator often fails to capture relative disparities between countries or the magnitude of their deviation from an optimal benchmark, thus limiting its analytical capacity for assessing systemic inequities.

Traditional approaches to composite index construction, based on arithmetic or geometric means, have been criticized for their rigidity and insensitivity to structural heterogeneity (Anand & Hanson, 1997; Salomon et al., 2012). To address these limitations, fuzzy logic–based models have emerged as a promising methodological alternative, offering greater flexibility to represent uncertainty and gradual transitions between health system states (Fullér & Majlender, 2001; Merigó & Gil-Lafuente, 2010; Yager, 1988). Within this family, the Generalized Ordered Weighted Logarithmic Aggregated Distance (GOWLAD) index (Alfaro-García et al., 2018) introduces a redistributive weighting scheme combined with logarithmic distance functions, allowing for a more nuanced measurement of inequality. This approach integrates mathematical rigor with interpretive sensitivity, providing a robust analytical basis for evaluating relative performance across countries.

The literature thus supports a progressive transition from static, additive measures toward adaptive, non-linear frameworks that reflect real-world disparities in a multidimensional space. The GOWLAD-based methodology adopted in this study builds upon these advances, applying fuzzy logic and logarithmic aggregation to assess the structural lag of OECD health systems from 2000 to 2021, thereby extending previous comparative approaches with a greater capacity to model inequality dynamics over time.

3. Materials and Methods.

This section describes the mathematical foundation and technical procedure used to estimate the health system performance of the countries analyzed through the GOWLAD index. First, the theoretical formalization of the operator is presented, highlighting its mathematical construction and key properties. The step-by-step implementation process is then detailed, including the transformations and operations required for its calculation. Finally, its practical application to the health systems of OECD countries is addressed, emphasizing methodological decisions such as data imputation and parameter selection. This structure is intended to facilitate replicability and enhance the analytical transparency of the study.

3.1. Mathematical formalization of the GOWLAD index and its adaptive version (GOWLAD*)

Comparative multicriteria analysis in complex systems, such as health systems, requires aggregation operators capable of coherently and robustly integrating multiple heterogeneous dimensions (Fullér & Majlender, 2001; Merigó & Gil-Lafuente, 2010; Yager, 1988). In this context, the GOWLAD index emerges as an advanced extension of the Ordered Weighted Averaging (OWA) operator, incorporating logarithmic distance measures and differentiated weightings (Alfaro-García et al., 2018).

The GOWLAD index compares each observed dimension with an optimal or reference value , capturing the relative distance from the ideal performance. Its general mathematical expression is defined as:

$$GOWLAD(x,y) = exp\left\{\left(\sum_{j=1}^{n} w_j\,[ln(b_j)]^{\lambda}\right)^{\frac{1}{\lambda}}\right\} \quad (1)$$

where:
x_j is the observed value for dimension .
y_j is the optimal value (maximum empirical value reached in the sample).
$b=_j | x_j- y_j|$ is the absolute distance between the observed value and the optimum
w_j is the weight assigned to dimension , with y .
λ is an aggregation parameter that regulates sensitivity to extreme deviations.

The parameter λ plays a crucial role in controlling the operator's sensitivity to extreme deviations. When λ=1, the index behaves as a weighted arithmetic mean in logarithmic scale; as λ → 0, it approaches a geometric mean; when λ→+∞, it focuses on the largest deviation (similar to a maximin criterion); and when λ→-∞, it focuses on the smallest deviation. This flexibility allows the index to adapt to different evaluative approaches depending on whether equity, efficiency, or extremes are to be emphasized.

The index structure ensures desirable properties in comparative evaluation contexts: the distance , defined as an absolute value, is always non-negative, allowing the application of the natural logarithm over a positive domain. The result of $ln(b_j)$ will be negative when $0<b_j<1$ and positive if $b_j>1$, ensuring that the index integrates both proximity to and departure from the optimum. This logarithmic transformation moderates the relative influence of each deviation and prevents dimensions with large magnitudes from distorting the aggregated result. The exponential function at the end of the expression restores the metric to a positive domain.

When all distances are strictly greater than zero ($b_j>0$ for all j), the formula can be applied without further adjustments representing a mathematically and empirically regular case in which no country exactly reaches the optimal value for any dimension, and the unit sum of weights w_j is preserved as defined by Alfaro-García et al. (2018).

However, situations may arise where for some dimension j, the absolute distance $b_j=|x_j-y_j|$ equals zero meaning the observed value exactly matches the optimal reference value. In such cases, $ln(b_j)$ is undefined, as the natural logarithm only admits strictly positive arguments ($b_j>0$), which prevents direct evaluation of the index in its original form. Simply omitting these terms would also remove their corresponding weights w_j, violating the unit-sum condition necessary to maintain structural proportionality across dimensions.

Under this circumstance, an adaptation of the original index is proposed, preserving its formal structure and ensuring its applicability in scenarios where certain dimensions present null gaps. The procedure consists of identifying the active dimensions, that is, those in which the absolute distance $b_j=|x_j-y_j|$ is strictly positive. These dimensions form the set:

$$A = \{j \in \{1,2,\dots,n\} | b_j > 0\} \quad (2)$$

To avoid indeterminacy, dimensions with b_j=0 are temporarily excluded from aggregation, and the weighting scheme is redefined solely over active dimensions. The adjusted weights w_j^* are computed as:

$$w_j^* = \frac{w_j}{\sum_{k \in A} w_k} \quad \forall j \in A \tag{3}$$

This redefinition preserves the relative proportionality of the original weights and ensures that $\sum_{k \in A} w_k{}^*$=1. The adjusted index, hereafter referred to as GOWLAD* (an adaptive version of the original index), is expressed as:

$$GOWLAD^*(x,y) = exp\left\{\left(\sum_{j \in A} w_j^* \cdot [ln(b_j)]^\lambda\right)^{1/\lambda}\right\} \tag{4}$$

The parameter λ retains its role within the adaptive index, operating over the active subset of dimensions without conceptual modification. This formulation maintains the original logic of weighted logarithmic distance aggregation while introducing an adjustment mechanism that guarantees mathematical continuity, even when certain dimensions reach optimal performance ($x_j = y_j$).

3.2. Technical procedure for estimating the GOWLAD index

Once the GOWLAD index is defined, the following section presents the technical and mathematical procedure for its implementation. This structure aims to facilitate the replicability of the model by guiding readers step by step through the process of obtaining the relative distances with respect to an empirical optimum.

Step 1. Data organization and preparation

Seven key indicators were defined, grouped into four conceptual blocks: human resources, medical technology, financing, and effective coverage. The data were obtained from official and standardized sources, primarily the Organization for Economic Co-operation and Development (OECD, 2023d, 2023a, 2023c, 2023e) and the World Health Organization (WHO, 2023a, 2023b, 2023c), ensuring international comparability and consistency. Detailed information for each indicator, together with its specific source and description, is presented later (see Table 1), allowing for the precise identification of data origins and reinforcing the transparency and replicability of the analysis.

Table 1. Description of the indicators included in the analysis, with definitions and official sources.

Variable	Description	Source
Med_10k	Medical doctors (per 10,000 population).	WHO Global Health Observatory (WHO, 2023a)
Beds_per_k	Hospital beds (per 1,000 population).	OECD Health Statistics (OECD, 2023d)
CT_per_m	CT scanners per 1,000,000 inhabitants.	OECD Health Statistics (OECD, 2023a)
OOP_Exp	Out-of-pocket expenditure as % of current health expenditure.	WHO Global Health Observatory (WHO, 2023b)
Exp_per_cap	Health expenditure per capita (USD, PPP).	OECD Health Statistics (OECD, 2023c)

Exp_GDP	Health expenditure as % of GDP.	OECD Health Statistics (OECD, 2023e)
UHC_Index	Universal Health Coverage (UHC) service coverage index.	WHO Global Health Observatory (WHO, 2023c)

Source: Authors' elaboration based on data from the World Health Organization (WHO, 2023a, 2023b, 2023c) and the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e).

To address missing values, the K-Nearest Neighbors (KNN) imputation method was applied, which estimates missing values by considering the multivariate similarity between observations and preserves the correlational structure of the dataset. Its application has been widely documented in health and bioinformatics studies (Beretta & Santaniello, 2016; Jerez et al., 2010; Troyanskaya et al., 2001).

The complete values for each country and year (2000, 2005, 2010, 2015, 2017, 2019, and 2021), obtained after KNN imputation, are presented in detail in Supplementary Tables S1 to S7 (see Supplementary Tables S1–S7). This imputed multi-year dataset, organized by country and indicator for each year, constitutes the structural basis on which the relative distances to the optimal values are calculated, as described in the following step.

Step 2. Identification of the optimal value

For each indicator, the empirical maximum value recorded in the set of countries and years analyzed (y_j) was identified, representing the best performance observed among the countries and years included in the analysis. In most cases, this corresponds to the maximum value; however, for some indicators, such as out-of-pocket expenditure as a percentage of total health expenditure (OOP_Exp), the optimal value is the minimum observed, since lower direct household spending represents better financial protection. This decision aligns with the recommendations of the WHO, which has emphasized that reducing out-of-pocket expenditure is key to strengthening universal coverage and equity (WHO, 2010). These criteria make it possible to build a homogeneous comparative framework and to establish a superior standard against which relative distances can be evaluated.

Table 2 summarizes the optimal values selected for each indicator in the years 2000, 2005, 2010, 2015, 2017, 2019, and 2021. For each year, a set of optimal values, one for each indicator, defines the empirical reference vector corresponding to the period. These values provide a homogeneous comparative framework against which the deviations observed in each country will be evaluated. Such deviations will be transformed into logarithmic distances following the formal procedure of the GOWLAD index, as described in the next step.

Table 2. Optimal reference values for each indicator and year (2000–2021)

Year	Med_10k	Beds_per_k	CT_per_m	OOP_Exp	Exp_per_cap	Exp_GDP	UHC_Index
2000	42.807	14.690	28.380	7.2734	4537.621	12.490	81.000
2005	49.990	14.080	51.540	7.3689	6432.954	14.579	83.000
2010	58.033	13.510	43.070	9.0956	7880.057	16.197	85.000
2015	59.099	13.170	59.540	10.0393	9355.406	16.401	90.000
2017	61.016	13.030	111.300	9.8950	10036.352	16.638	90.000
2019	62.472	12.800	69.810	9.5877	10849.874	16.553	91.000
2021	71.516	12.770	71.590	8.7383	12292.892	17.299	91.000

Source: Authors' elaboration based on data from the World Health Organization (WHO, 2023a, 2023b, 2023c) and the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e).

Step 3. Estimation of the logarithmic distance

Based on the observed values (x_j) and the defined optimal values (y_j), the absolute distance for each dimension is calculated using the expression $b_j=|x_j-y_j|$. These distances represent the degree of deviation of each country from the optimal performance in each indicator. The annual results of these distances are presented in Supplementary Tables S8 to S14, organized by year and dimension.

Since the GOWLAD index uses logarithmic transformations to differentially weight the degrees of deviation, it is necessary to ensure that the values are strictly positive. For cases in which $x_j = y_j$, the criterion of assigning $ln(b_j) = 0$ is adopted, which avoids the mathematical indeterminacy of $ln(0)$. This treatment is consistent with the corrective logic of the model, as a zero distance from the optimum implies no penalization.

Subsequently, the b_j values are reordered from highest to lowest so that the dimensions furthest from the optimum receive greater weight in the aggregation process. This reordered set is then subjected to the natural logarithmic transformation, obtaining the $ln(b_j)$ values, which make it possible to compress small differences and amplify significant deviations. This operation favors a more sensitive interpretation of critical inequalities among countries.

In order to facilitate reading and comparative analysis, from this point onward a simplified notation will be adopted to refer to the ordered distances. We will denote b_1 as the highest distance (i.e., the dimension furthest from the optimum for a given country) and b_7 as the lowest (the one with the smallest deviation). This convention will be maintained in the following steps to improve the traceability of the aggregation process, regardless of the original indicator to which each dimension corresponds.

Table 3 shows this procedure applied to the year 2021 for a representative sample of ten countries. It includes the reordered absolute distances from highest to lowest and their respective logarithmic transformations. These estimates prepare the ground for the next stage of the model, in which the sensitivity parameters and the redistributive weights are incorporated into the final calculation of the index.

Table 3. Reordered absolute distances and their logarithmic transformation for a selected sample (2021)

Country	b1	b2	b3	b4	b5	b6	b7	lnb1	lnb2	lnb3	lnb4	lnb5	lnb6	lnb7
USA	35.43	28.97	10.00	5.00	2.09	0.00	0.00	3.57	3.37	2.30	1.61	0.74	0.00	0.00
AUS	5912.88	31.70	8.73	6.87	5.10	4.00	0.00	8.68	3.46	2.17	1.93	1.63	1.39	0.00
CAN	5476.43	46.88	45.07	10.19	5.21	4.88	0.00	8.61	3.85	3.81	2.32	1.65	1.59	0.00
ESP	8020.35	50.08	26.72	10.61	9.80	6.99	6.00	8.99	3.91	3.29	2.36	2.28	1.94	1.79
SVK	9393.77	51.74	34.72	10.67	9.54	9.00	7.09	9.15	3.95	3.55	2.37	2.26	2.20	1.96
ITA	7872.34	32.59	30.54	13.99	9.65	7.95	7.00	8.97	3.48	3.42	2.64	2.27	2.07	1.95
PRT	8147.80	41.41	20.67	13.85	9.28	6.18	3.00	9.01	3.72	3.03	2.63	2.23	1.82	1.10
MEX	11014.39	64.12	45.92	32.63	16.00	11.77	11.41	9.31	4.16	3.83	3.49	2.77	2.47	2.43
CHL	9463.56	47.95	41.79	23.90	10.82	9.00	7.58	9.16	3.87	3.73	3.17	2.38	2.20	2.03
COL	10670.20	56.69	47.00	11.00	10.10	8.28	4.93	9.28	4.04	3.85	2.40	2.31	2.11	1.60

Source: Authors' elaboration based on data from the World Health Organization (WHO, 2023a, 2023b, 2023c) and the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e), following the methodological framework of Alfaro-García et al. (2018)

Step 4. Exponential transformation using the λ parameter

Once the reordered absolute distances and their logarithmic transformations $\left(\ln(b_j)\right)$ have been obtained, an additional transformation is applied using a sensitivity parameter λ. This operation consists of raising each $ln(b_j)$ value to the power λ, generating a new set of values that reflect the degree of differential penalization assigned to each deviation.

In this study, λ = 2 was adopted as the transformation parameter, given its ability to moderately intensify relevant deviations without overreacting to extreme values. This choice is inspired by the general approach of Alfaro-García et al. (2018), who emphasize that the λ parameter acts as a sensitivity modulator in the aggregation process, allowing the penalization assigned to the gaps to be adjusted according to their magnitude. By selecting an intermediate value of 2, an analytical balance is achieved between methodological robustness and differentiated attention to the most severe inequalities, in line with the distributive objectives of the GOWLAD index.

This transformation, however, should not be interpreted as a form of weighting in itself. Unlike the weight vector that will be applied later, the λ parameter acts as a structural sensitivity modulator that prepares the data for aggregation without incorporating exogenous assumptions about the relative importance of the dimensions. By intensifying the most relevant gaps and attenuating the smaller ones, it allows the subsequent assignment of redistributive weights to be applied on a methodologically coherent and previously scaled basis.

The estimates resulting from this procedure are presented in Table 4, corresponding to the year 2021 and a representative sample of ten countries. The table shows the logarithmic values of the reordered absolute distances (lnb_j) and their transformation using the λ parameter, i.e., $[ln(b_j)]^{\lambda}$. This table constitutes the final input prior to the assignment of redistributive weights and makes it possible to clearly observe how the transformation differentially amplifies the most significant deviations, in line with the corrective logic of the model.

Table 4. Logarithmic distances and their transformation with parameter λ=2, selected sample (2021)

Country	$(lnb_1)^{\lambda}$	$(lnb_2)^{\lambda}$	$(lnb_3)^{\lambda}$	$(lnb_4)^{\lambda}$	$(lnb_5)^{\lambda}$	$(lnb_6)^{\lambda}$	$(lnb_7)^{\lambda}$
USA	12.73	11.33	5.30	2.59	0.55	0.00	0.00
AUS	75.43	11.95	4.70	3.72	2.65	1.92	0.00
CAN	74.10	14.80	14.50	5.39	2.72	2.51	0.00
ESP	80.82	15.32	10.79	5.58	5.21	3.78	3.21
SVK	83.68	15.57	12.58	5.60	5.09	4.83	3.84
ITA	80.48	12.14	11.69	6.96	5.14	4.30	3.79
PRT	81.10	13.87	9.17	6.91	4.96	3.31	1.21
MEX	86.62	17.31	14.65	12.15	7.69	6.08	5.93
CHL	83.82	14.98	13.93	10.07	5.67	4.83	4.10
COL	86.03	16.30	14.82	5.75	5.35	4.47	2.55

Source: Authors' elaboration based on data from the World Health Organization (WHO, 2023a, 2023b, 2023c) and the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e), following the methodological framework of Alfaro-García et al. (2018)

Step 5. Application of corrective distributive logic and weight rescaling

The resulting logarithmic distance is multiplied by the weight corresponding to each dimension, which allows the relative importance of each deviation from the optimum to be reflected. Unlike other multicriteria approaches that assign weights based on fixed thematic criteria or external preferences, this study adopts a logic of increasing penalization applied to the descending order of absolute distances, following the structure of the GOWLAD operator. This strategy assigns greater weight to the dimensions furthest from the optimum, with the objective of amplifying their influence in the final aggregation of the index.

The weighting vector used is: w_j=[0.30,0.20,0.16,0.12,0.09,0.08,0.05], it is normatively defined to reflect this increasing penalization. Although this pattern is not directly derived from a universal mathematical formula, it is supported by recommendations from international organizations. The WHO (2010) emphasizes the need to prioritize closing critical gaps, such as those related to out-of-pocket expenditure, due to their direct impact on equity and financial protection. Similarly, the OECD (2023b) warns that national averages can mask structural inequalities that must be explicitly identified. Finally, Boerma et al. (2014) propose that composite health indices should include mechanisms to prevent the dilution of severe deficiencies in the aggregation process. Thus, the adopted weighting structure does not respond exclusively to a technical rationale but incorporates a normative stance that prioritizes health equity in comparative contexts.

When one or more dimensions reach their optimal value ($b_j = 0$), their influence is removed from the aggregation to avoid logarithmic indeterminacies and maintain distributive coherence. In these cases, the original weights are rescaled exclusively among the active dimensions $A=\{j\in\{1,\dots,n\} | b_j > 0\}$, using the formula:

$$w_j^* = \frac{w_j}{\sum_{k\in A} w_k}, \forall j \in A$$

Table 5 presents the calculation of the rescaled weights w_j^* for the case of the United States in 2021, where two dimensions present zero gaps (b_j=0) and are excluded from weighting.

Table 5. Weight adjustment under active dimension restriction in the GOWLAD* index (USA example, 2021)

b_j **(absolute deviation)**	w_j **(original weight)**	w_j^* **(adjusted weight)**
35.43	0.30	0.345
28.97	0.20	0.230
10.00	0.16	0.184
5.00	0.12	0.138
2.09	0.09	0.103
0.00	0.08	------
0.00	0.05	-------
Total Active	0.87	1

Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

Once the adjusted redistributive weights w_j^* have been determined for the active subset of relevant dimensions in each country, they are multiplied by the previously obtained transformed values $ln(b_j)^\lambda$. This operation allows the estimation of the weighted contributions per dimension, which will later be aggregated through the global logarithmic function of the GOWLAD index.

It is worth noting that, for the analyzed sample, three distinct configurations of w_j^* vectors were identified: five countries presented a single dimension with an optimal value ($b_j = 0$), one country presented two, and the remaining four had no match with the optimum, thus retaining the original weights ($w_j^* = w_j$). Table 6 presents the weighted products $ln(b_j)^\lambda \cdot w_j^*$ for each of the considered distances, corresponding to the ten OECD countries selected for the year 2021.

Table 6. Transformed and weighted values of absolute deviations using $\left(ln(b_j)^\lambda \cdot wj^*\right)$ for a sample of 10 OECD countries (2021)

Country	$(lnb_1)^\lambda \cdot w_1$	$(lnb_2)^\lambda \cdot w_2$	$(lnb_3)^\lambda \cdot w_3$	$(lnb_4)^\lambda \cdot w_4$	$(lnb_5)^\lambda \cdot w_5$	$(lnb_6)^\lambda \cdot w_6$	$(lnb_7)^\lambda \cdot w_7$
USA**	4.389	2.605	0.975	0.357	0.057	0.000	0.000
AUS**	23.819	2.515	0.791	0.469	0.251	0.162	0.000
CAN	23.400	3.117	2.442	0.681	0.258	0.212	0.000
ESP	24.245	3.063	1.727	0.669	0.469	0.302	0.161
SVK	25.105	3.115	2.013	0.672	0.458	0.386	0.192
ITA	24.144	2.428	1.871	0.835	0.463	0.344	0.189
PRT	24.330	2.773	1.468	0.829	0.447	0.265	0.060
MEX	25.986	3.462	2.343	1.458	0.692	0.486	0.296
CHL	25.145	2.995	2.229	1.209	0.510	0.386	0.205
COL	25.809	3.260	2.372	0.690	0.481	0.358	0.127

Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

Once the weighted products $ln(b_j)^\lambda \cdot w_j^*$ are obtained for each distance and each country, they are aggregated using the logarithmic function defined by the GOWLAD* index. This operation synthesizes the multidimensional deviations into a single value per country, capturing both the relative magnitude of each gap and its structural weight within the system. The resulting values represent the generalized distance from the empirical optimum, thus enabling a comprehensive comparison of health system performance under a logic of equitable and normatively informed penalization.

*Step 6. Final calculation of the GOWLAD**

The final step in estimating the GOWLAD* index consists of integrating, for each country, the values previously transformed using the natural logarithm and weighted with the adjusted weights w_j^*, in order to generate a single synthetic value that reflects its relative distance from the optimal health system performance profile.

This is carried out through a sequence of three linked operations. First, the total sum of the products $ln(b_j)^\lambda \cdot w_j^*$ is calculated, considering only the active distances for each country, that is, those for which the difference between the observed value and the optimal value is not zero. Next, this accumulated value is raised to the $\lambda - th$ root, which in our case is equivalent to a square root, since λ = 2 has been defined. Finally, the exponential function is applied to the resulting value, thereby transforming it into a directly interpretable scale that quantifies the aggregated distance to the empirical optimum.

Table 7 presents the result of this procedure for the ten countries selected as the reference sample throughout the methodological section. For each country, it includes the value of the weighted sum of logarithmic distances, the result after applying the square root, and the final GOWLAD* index resulting from the exponential transformation. This presentation makes it possible to clearly observe the complete aggregation process and how the index synthesizes the weighted health gaps based on the most efficient empirical performance.

Table 7. Final GOWLAD* index scores for ten OECD countries (2021)

Country	*Sum* $\ln(b_j)^{\lambda} \cdot w_j^{*}$	*Square root* (λ = 2)	*GOWLAD*=exp(root)*
USA	8.3829	2.8953	18.0895
AUS	28.0080	5.2923	198.7921
CAN	30.1096	5.4872	241.5856
ESP	30.6358	5.5350	253.3979
SVK	31.9408	5.6516	284.7518
ITA	30.2734	5.5021	245.2123
PRT	30.1718	5.4929	242.9573
MEX	34.7236	5.8927	362.3734
CHL	32.6804	5.7167	303.8943
COL	33.0973	5.7530	315.1422

Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

With the calculation of the GOWLAD* index, the technical procedure of weighted logarithmic aggregation based on fuzzy logic is concluded. This procedure has been developed progressively, incorporating logarithmic transformations, reordering of distances, weight adjustments over active subsets, and a non-linear aggregation operation sensitive to the distribution of performances.

The resulting GOWLAD* value for each country synthesizes its aggregated distance from an empirical optimum derived from the best values observed in the sample. This distance is interpreted as a composite indicator of relative performance: the smaller its magnitude, the closer the country is considered to be to the optimal profile. Although no fixed threshold is established as a universal reference, values close to one tend to indicate an almost complete alignment with desirable standards, while increasing values reflect the accumulation of gaps across multiple dimensions.

This approach enables a relative and context-sensitive interpretation of health system performance, preserving the priority structure established in the weights and respecting the constraints associated with handling optimal values. The following section will present the empirical results derived from the application of the GOWLAD* index to OECD countries during the period 2000–2021, allowing for a comparative reading of trajectories and persistent gaps.

3. Analysis and Discussion of Results.

Once the technical procedure described in the previous section has been completed, the results of the GOWLAD* index are presented for 36 OECD countries over the period 2000–2021. This index estimates the weighted logarithmic distance between each country's health system performance and an empirical optimal benchmark constructed from the best values observed in each dimension. Unlike an absolute metric, GOWLAD* reflects a relative measure of performance: low values indicate greater proximity to the optimal profile, whereas high values denote more pronounced structural gaps.

Table 8 synthesizes the index values for seven selected years (2000, 2005, 2010, 2015, 2017, 2019, and 2021) and incorporates three additional indicators that allow the evolution of each country to be examined: the multi-year average, the net change between the beginning and the end of the period, and the standard deviation, which is useful for identifying stable or volatile trajectories. This information makes it possible to identify patterns of convergence, persistence of gaps, or relative improvements within the set of countries analyzed.

Table 8. GOWLAD index across OECD countries for selected years between 2000 and 2021

Country	2000	2005	2010	2015	2017	2019	2021
AUS	121.0497	190.0992	211.0142	169.0118	190.2357	186.5539	198.7921
AUT	82.5907	122.9511	128.2194	155.3296	189.0268	172.2725	178.5868
BEL	105.2805	152.9840	163.7520	178.7258	212.3570	198.4966	217.5121
CAN	106.6203	146.7140	155.4451	209.8727	240.5823	243.7170	241.5856
CHL	178.7643	239.2705	243.2424	268.0384	298.9320	279.9053	303.8943
COL	157.3321	195.2742	227.8268	273.5481	311.7156	299.7227	315.1422
CRI	174.2201	210.8436	229.8469	270.5684	308.6794	294.9918	321.7597
CZE	127.1245	175.5921	187.5520	222.0887	254.2503	234.7069	242.3703
DNK	108.8666	152.9723	141.9152	165.2191	202.7046	182.7336	193.9545
EST	159.5932	216.9966	218.2534	246.4057	286.8917	268.8151	288.4382
FIN	113.2715	163.1436	189.5928	194.9703	233.2629	222.9032	236.4090
FRA	100.6183	154.4807	151.4108	205.4197	241.8060	204.3805	243.3082
DEU	74.1339	140.2354	143.2918	144.8905	172.2858	152.1125	161.4142
GRC	161.1784	192.0318	187.2505	249.2105	300.0055	270.5933	254.5273
HUN	154.7211	201.0843	226.1490	258.2287	295.9968	284.1199	303.5558
ISL	87.2997	154.0864	174.9036	182.1218	219.7526	193.8230	215.4871
IRL	124.0164	148.9849	152.9273	195.9904	227.7733	212.0821	225.2997
ISR	136.8619	193.1331	210.6271	241.7879	276.7362	264.3960	287.5131
ITA	115.1417	154.9498	162.7951	204.0757	245.0874	225.0241	245.2123
JPN	142.1834	180.9161	197.1788	201.9490	225.9815	230.4524	229.2392
LVA	188.3136	226.4807	232.1137	259.7640	305.0756	273.7837	279.9653
LTU	168.6135	220.7067	219.7485	248.0515	285.5307	259.0388	276.1664
LUX	71.3606	100.2251	119.3712	215.2963	221.7118	233.2817	224.6680
MEX	199.1481	258.8490	270.4402	300.1671	345.7307	335.0211	362.3734
NLD	95.9782	141.3754	170.4324	178.4083	209.1502	194.2208	203.7850
NZL	129.2966	170.4532	178.7014	207.2335	240.4180	229.5953	222.4278
NOR	89.5043	129.4380	147.7391	146.7912	177.3128	158.4222	174.2101
POL	172.5216	222.8548	227.2722	254.1770	292.7817	267.1921	289.9969

PRT	129.4999	162.4408	210.9712	218.6328	251.8404	229.9590	242.9573
PRK	191.3561	210.6532	206.9881	228.9109	267.3366	240.3423	293.5244
SVK	144.1009	200.6908	204.8324	233.3526	277.7592	264.3669	284.7518
SVN	134.1224	184.5545	199.2031	229.7226	262.1496	239.4264	259.3320
ESP	137.0103	169.1730	184.6113	216.3888	252.6308	233.2493	253.3979
SWE	108.4413	153.6598	161.5367	170.2745	204.3863	188.2192	210.0298
CHE	78.5901	124.1996	124.1302	133.0376	166.1028	151.2175	166.6073
TUR	185.0012	238.3675	248.3037	276.1116	318.3810	304.2892	329.3847
GBR	132.5360	165.8903	177.5042	198.4824	227.4721	219.6058	217.4851
USA	10.5876	16.2690	14.8482	11.6399	21.0205	15.7301	18.0895
OECD	128.8644	173.2375	184.2616	209.5762	243.7067	227.8622	242.4514

Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

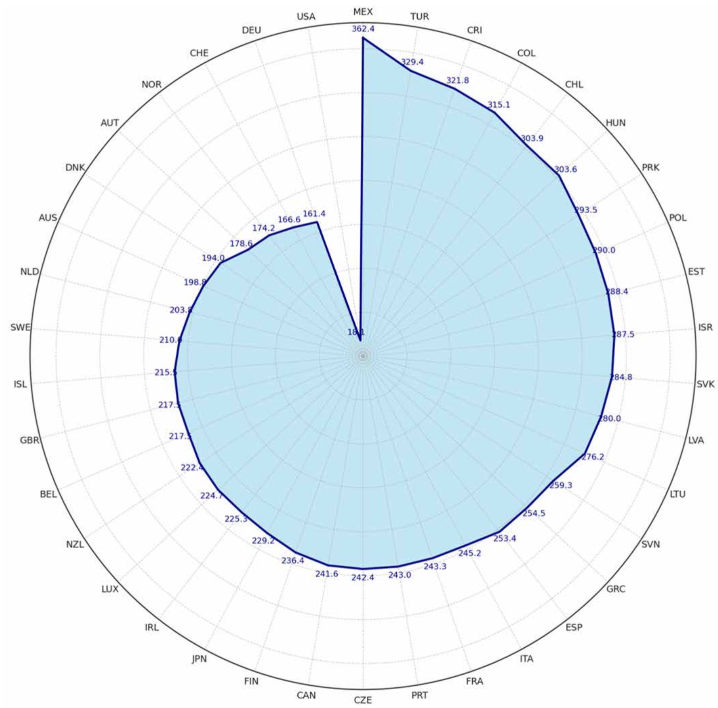
Among the most consistent findings, the sustained position of the United States stands out as the country closest to the empirical optimum, with the lowest GOWLAD* values in all periods. Germany, Switzerland, and Norway also maintain stable trajectories close to the optimum, systematically remaining below the OECD average. In contrast, Mexico, Latvia, Colombia, and Turkey exhibit persistently high index values, evidencing significant structural gaps in their health systems. This pattern of polarization suggests the coexistence of clusters of advanced performance and areas of accumulated lag within the evaluated set.

To highlight the most recent landscape of health system performance, Figure 1 presents the GOWLAD* index values for the year 2021, ordered from the greatest to the smallest distance from the empirical optimal profile. This representation facilitates comparison across countries by clearly displaying the most critical divergences: those closest to the desirable standard and those with significant lags. Unlike Table 8, which addresses a multi-year perspective, this figure enables a synchronic reading of the current state of health system performance.

Figure 2 expands the multi-year analysis of the GOWLAD* index by representing, longitudinally, the trajectories of relative distance for 36 OECD countries during the 2000–2021 period, with snapshots taken at seven representative years. This visualization allows for the identification of comparative dynamics in health system performance, including stable trajectories, progressive improvements, or persistent lags. The inclusion of the OECD average line provides an additional benchmark for assessing each country's relative position within the regional set.

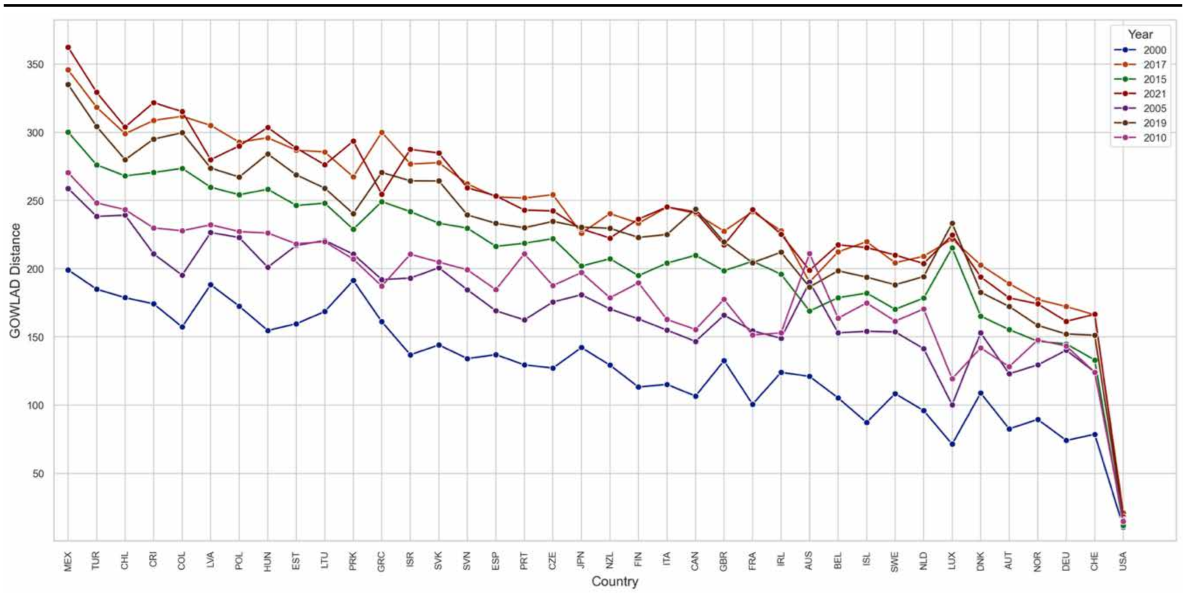
A notable pattern is the persistence of a subset of countries whose distance from the empirical optimal profile has remained consistently above the OECD average. This group includes Mexico, Turkey, Colombia, Latvia, and Chile, whose trajectories reflect structural gaps in health system performance with no clear signs of sustained reduction. Mexico, in particular, consistently exhibits the highest GOWLAD* index value, indicating an accumulated lag relative to the reference vector. Although initial oscillations can be observed, the overall trend for this group is stability at high distance levels.

Figure 1. GOWLAD index for OECD countries in 2021, ranked from highest to lowest relative distance to the optimum.



Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

Figure 2. Longitudinal trajectories of the GOWLAD index for OECD countries, 2000–2021, with OECD average reference line.



Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

At the opposite extreme, a smaller group of countries has maintained continuous proximity to the empirical optimum, notably Switzerland, Germany, Norway, and the United States. These low GOWLAD* index values reflect a sustained pattern of favorable performance in the evaluated dimensions. This stability can be interpreted as evidence of relatively consolidated systems, at least from the structural perspective covered by the index.

The OECD regional average shows a slight decline over the period, which could be interpreted as an aggregate approach to the optimum. However, this improvement is not uniform: while countries such as South Korea, Portugal, and Slovenia show consistent downward trajectories, others such as Luxembourg or Greece display oscillations and partial setbacks. These differences suggest that health system convergence within the OECD remains limited and heterogeneous.

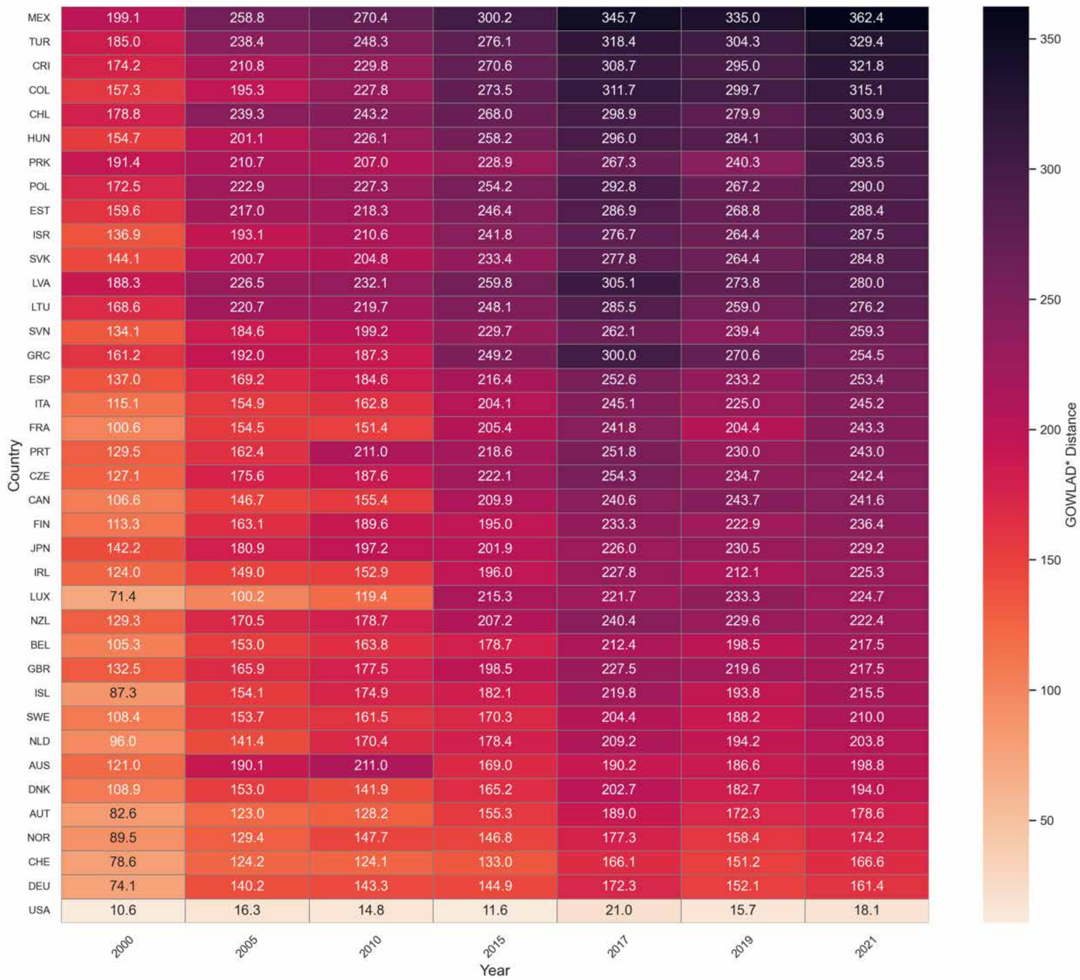
In summary, Figure 2 reveals the persistence of structural differences between groups of countries. While some trajectories point to a gradual approach toward the empirical optimum, others remain distant, without sustained progress. This heterogeneity does not necessarily constitute polarization in the strict sense, which would require additional statistical verification, but it does show a pattern of relative divergence between the extremes of the set. The visualization thus reinforces the usefulness of the GOWLAD* index as a diagnostic tool for the longitudinal monitoring of structural gaps in public health.

Figure 3 complements the longitudinal analysis in Figure 2 by providing a synchronic, ordered visualization of the GOWLAD* index through a heatmap. In this representation, countries are arranged from highest to lowest according to their multi-year average, enabling the immediate observation of the structural persistence of relative lags in health system performance. This type of visualization emphasizes not individual trajectories, but patterns of regularity, disruption, or convergence among countries and periods.

The heatmap facilitates the detection of three key phenomena: (1) countries with persistent structural lag, such as Mexico, Turkey, and Colombia, whose cells consistently display high values over time; (2) trajectories of progressive improvement or partial recovery, as observed in South Korea or Greece, where the most intense tones diminish in recent years; and (3) cases of instability or reversal, such as Luxembourg or Japan, where variations do not follow a defined direction. This representation, therefore, makes it possible to visualize OECD heterogeneity not only as differences in levels but also as differences in temporal dynamics.

A boxplot was constructed to represent the evolution of dispersion in the GOWLAD* index among OECD countries between 2000 and 2021 (Figure 4). This visualization allows for the analysis of the overall distribution of health system performance without focusing on individual countries, capturing structural trends such as the median, the interquartile range, and the presence of outliers. From 2010 onward, a sustained upward shift in the median is observed, suggesting a collective movement away from the empirical optimum, consistent with previous findings.

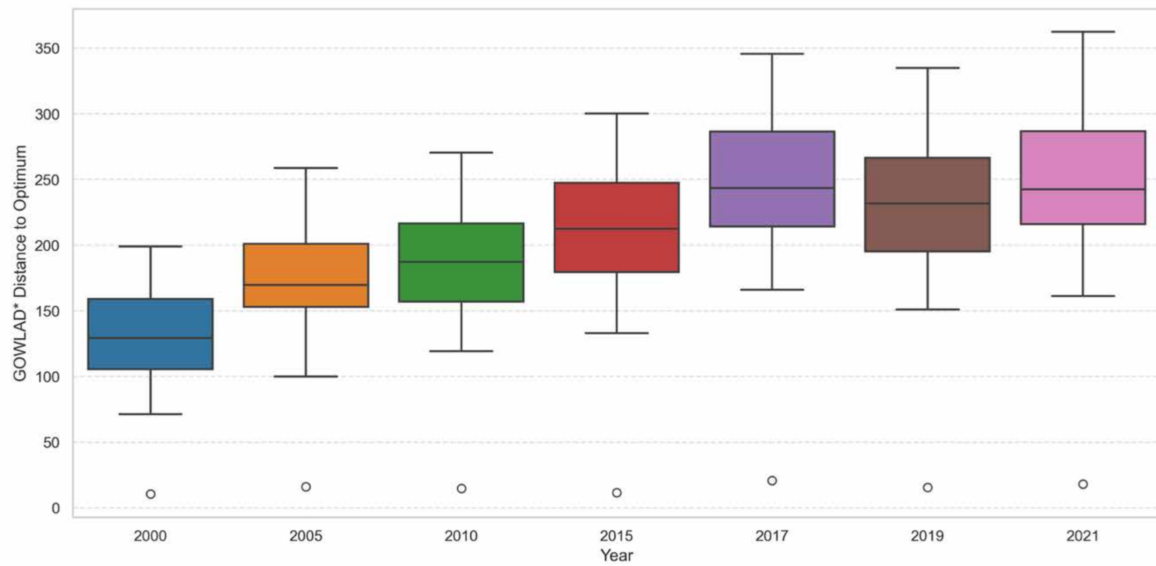
Figure 3. Multiyear heatmap of the GOWLAD index for OECD countries, 2000–2021.



Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

Furthermore, during the years 2010 and 2015, a notable widening of the interquartile range can be observed, reflecting an increase in relative inequality between countries. Recurrent lower outliers stand out, corresponding to countries with performance close to the optimum, while no upper outliers are identified, indicating the absence of extreme lags. This asymmetry in the distribution suggests that the distancing from the optimum has been shared in a generalized manner, rather than being concentrated in just a few cases. Overall, Figure 4 provides evidence that, despite advances in public health over the past two decades, there has been no clear trend toward convergence in health system performance among OECD countries. On the contrary, the GOWLAD* index reveals a persistent relative dispersion and a sustained departure from the empirical optimum, suggesting that improvements have not been sufficient to reduce structural efficiency gaps between health systems.

Figure 4. Boxplot of the GOWLAD index for OECD countries in seven benchmark years (2000–2021).



Source: Authors' elaboration based on calculations using the GOWLAD* model (Alfaro-García et al., 2018) and data from the Organization for Economic Co-operation and Development (OECD, 2023a, 2023c, 2023d, 2023e) and World Health Organization (WHO, 2023a, 2023b, 2023c).

Taken as a whole, the empirical results obtained through the GOWLAD* index reveal a sustained trajectory of distancing from the empirical optimum in most of the countries analyzed, with increasing structural dispersion from 2010 onward. The visualizations presented (radar, heatmap, and boxplot) confirm that individual advances in public health have not led to systemic convergence but rather to a shared and cumulative lag. This evidence constitutes a fundamental starting point for reflecting, in the following section, on the structural, institutional, and methodological factors that could be explaining this phenomenon, as well as on the ethical implications that emerge when incorporating artificial intelligence and complex models into the evaluation of health system performance.

Conclusions.

This study set out to evaluate the structural performance of OECD health systems between 2000 and 2021 using the GOWLAD* index—a fuzzy logic–based, weighted logarithmic aggregation model designed to capture multidimensional disparities. The results confirm that the methodological objective was achieved: the model effectively quantified the relative distance of each country's health system from an empirical optimum, integrating both structural and financial dimensions under a dynamic, year-specific benchmark.

The empirical evidence shows persistent and, in some cases, widening disparities among OECD countries. Mexico, Turkey, and Colombia consistently remained farthest from the empirical optimum, while Switzerland, Germany, Norway, and the United States exhibited sustained proximity to it. These findings indicate that improvements in isolated indicators, such as health expenditure or service coverage, have not translated into systemic convergence when assessed through a multidimensional and non-linear framework.

Methodologically, the GOWLAD* index demonstrated strong analytical capacity to reveal latent inefficiencies masked by conventional averaging methods. By emphasizing the weakest dimensions, it allows a more precise identification of structural weaknesses. However, this sensitivity also calls for interpretive prudence: the index accentuates disparities in systems with uneven internal performance and should therefore be used primarily as a diagnostic and comparative monitoring tool, not as a rigid ranking device.

The persistence of structural lag across certain countries underscores the limitations of traditional policy approaches centered on expenditure expansion or regulatory reform. Broader institutional and socioeconomic asymmetries, such as governance fragmentation, inequality, and technological capacity, continue to constrain systemic equity. The results thus advocate for a more integrated approach to health governance, combining financial investment, institutional strengthening, and innovation to reduce long-term structural gaps.

Future research should extend the application of the GOWLAD* framework to non-OECD contexts, test alternative weighting schemes and λ parameters, and incorporate emerging dimensions such as resilience, digital transformation, and adaptive capacity to shocks. These extensions would further validate the robustness of the model and its relevance for policy evaluation in complex environments.

In conclusion, the study fulfilled its primary objective by providing a multidimensional, sensitivity-adjusted assessment of health system performance. The evidence demonstrates that achieving structural convergence requires more than improving isolated indicators: it demands addressing the deep institutional and social asymmetries that shape systemic inequality. The GOWLAD* index contributes to this endeavor by offering a mathematically rigorous and ethically grounded tool to guide public health evaluation and policymaking toward greater fairness and structural coherence.

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