RESILIENCE OF EUROPEAN HEALTHCARE SYSTEMS DURING THE PANDEMIC: LESSONS AND PERSPECTIVES FOR HEALTHCARE MANAGEMENT

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Abstract
The COVID-19 pandemic has severely tested the resilience of European healthcare systems, exposing vulnerabilities but also generating valuable lessons for future health management. This study analyses the evolution of infections, deaths, and fatality rates in 46 European countries between 2020 and 2024, using data from the World Health Organization and Our World in Data. Employing quantitative methods and statistical models (linear, quadratic, and power regression), the research explores the relationship between confirmed cases and mortality, assessing the extent to which resilience mechanisms influenced outcomes. Results show that while mortality increased with the number of infections, resilience measures significantly reduced fatality rates over time. The power model best explained the case-death relationship, highlighting sub-proportional growth of mortality in relation to infections, a sign of adaptive system capacity. Findings demonstrate that resilience is not an abstract concept but a measurable determinant of health outcomes, directly linked to preparedness, adaptability, and equity. The study concludes with three key lessons for future healthcare management: institutionalizing resilience, strengthening adaptability, and investing in equity and prevention. These elements are crucial to ensure that European health systems can effectively respond to future crises and safeguard population health.

Keywords
Management, Resilience, Health system, Pandemic, Covid-19, Health management and planning

JEL Classification
H12, H51, H84, I18

Introduction

In this article, we present a detailed analysis of the beginning and end periods (2020-2024) of the COVID-19 pandemic in Europe, focusing on the differences and particularities of each country. The study is based on an assessment of the number of

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people infected with the SARS-CoV-2 virus and the number of associated deaths, these two dimensions being the main indicators in measuring the impact of the pandemic.

By correlating these data, we can determine the fatality rate and then, through systematic comparison, analyze the impact of healthcare system resilience on fatality over time. The central objective of the research is to understand the extent to which health resilience has contributed to reducing fatality and protecting the health of the European population, as well as to draw useful lessons for strengthening the capacity to respond to future crises.

The COVID-19 pandemic has exposed major vulnerabilities in health systems around the world. As of June 23, 2021, more than 178 million people had been infected with the new SARS-CoV-2 coronavirus, with nearly 3.9 million deaths reported. The consequences have been far-reaching, with unprecedented disruptions to health services and dramatic social and economic effects. The global economy has entered a recession estimated at $8.8 trillion, and populations already in situations of fragility, conflict and violence have felt the disproportionate impact of this crisis (WHO, 2021a).

This context highlighted that traditional efforts to strengthen health systems, previously considered fundamental to achieving universal coverage goals, did not include sufficient investment in essential public health functions and health commons. In the absence of updated and adequately funded plans, most countries have responded reactively rather than proactively to the events generated by the pandemic (WHO, 2024a).

1. Review of the scientific literature

To better understand the concept of health resilience, it is necessary to refer to the definitions proposed by international organizations. According to the World Health Organization, health systems are made up of people and actions whose main purpose is to improve health, organized into six interconnected components: leadership and governance, financing, health workforce, health information, medicines and technologies, infrastructure, and service delivery. All these elements are interdependent and must work together to effectively meet the needs of the population (WHO, 2021b).

Health system resilience refers to the capacity of institutions, infrastructure, and communities to anticipate, prevent, prepare for, absorb, adapt to, and recover from shocks and stresses while maintaining the delivery of essential health services. It also involves constantly learning from experience and integrating lessons into future processes so that the system improves its performance and becomes stronger in any context (WHO, 2024b).

Building resilience is not limited to the emergency response phase, but covers the entire resilience cycle: prevention, preparedness, response, adaptation, and recovery. Prevention aims to reduce structural vulnerabilities and potential risks; preparedness is achieved through the development of continuity plans, staff training, and the organization of simulations and practical exercises; response involves activating plans based on well-defined criteria and triggers, mobilizing resources, and ensuring the continuity of essential services; adaptation consists of adjusting actions and the flexibility of interventions according to the context of the crisis; recovery and learning are achieved through post-event assessments, documenting lessons learned, and updating plans (WHO, 2021a).

Testing plans play a central role in the functionality of resilience. Simulation exercises and audits allow staff to practice procedures and familiarize themselves with their roles, contributing to effective communication between all actors involved. At the same time, these exercises help identify gaps and obstacles, which can then be corrected by updating the plans. Plans should be activated based on clear triggers, such as a healthcare facility exceeding its capacity, and a breaking point should be defined for each plan—the moment when available resources can no longer support essential functions and external support is needed.

Resilience cannot be conceived as an isolated attribute, but must be an integral part of health system planning and development. Institutionalizing this concept requires integrating it into national strategies, public policies, and health plans, with the allocation of necessary resources. Roles and responsibilities must be clearly defined at all levels, and governance and coordination mechanisms must allow for the participation of all relevant actors. (WHO, 2024a)

Recent experiences, including the Ebola epidemic and the COVID-19 pandemic, have shown that the lack of a systematic and proactive approach to resilience leads to increased vulnerability and high costs. Therefore, strengthening resilience should be seen as a continuous process, developed through learning and the constant integration of lessons learned (Thomas et al., 2020). Only in this way can health systems respond effectively to future shocks while ensuring the provision of essential services to the entire population.

In recent years, scientific literature has redefined the concept of healthcare system resilience, moving beyond a static view based solely on the ability to absorb shocks. Recent studies have emphasised that resilience should be understood as a dynamic and multidimensional capacity, not only as an immediate response to crises, but also as adaptation, organisational learning and the transformation of healthcare systems over time (Kruk et al., 2020; Haldane et al., 2021). From this point of view, adaptive governance plays a central role: the ability of institutions to quickly change strategies, reallocate resources and update clinical protocols is considered a key determinant of resilience (Belloni et al., 2025).

The most recent literature also highlights that resilience cannot be assessed only through qualitative or conceptual tools, but must be measured using observable indicators of healthcare system performance (Papanicolas et al., 2025), such as: the continuity of essential services, equitable access to care and changes in mortality rates during a health crisis provide concrete elements for assessing the level of resilience achieved. In this sense, resilience emerges as a measurable and comparable characteristic between different national contexts, rather than as a purely theoretical concept.

Empirical analyses conducted in Europe during the COVID-19 pandemic show significant differences in mortality outcomes between countries, which cannot be explained exclusively by epidemiological factors. Numerous studies have highlighted how the responsiveness of healthcare systems, the speed of implementation of public health measures and the effectiveness of vaccination campaigns have had a direct impact on reducing mortality associated with the virus (Legido-Quigley et al., 2022; Elkomy et al., 2024). In particular, systems characterised by greater organisational resilience showed a more rapid reduction in fatality rates, even in the presence of high levels of infection.

Several studies also emphasise that the resilience of healthcare systems is closely linked to structural factors such as the availability of healthcare personnel, the capacity of intensive care units and the quality of healthcare information systems (Perone, 2025). These elements have enabled some European countries to mitigate the direct relationship between the number of cases and the number of deaths, demonstrating that mortality is not an inevitable outcome of increased infections, but can be contained through appropriate management and adaptation strategies. From this perspective, resilience becomes an intermediate factor between the spread of the virus and the final health outcomes.

In recent literature, the case fatality rate (CFR) is frequently used as an indirect indicator of healthcare system performance during the pandemic: a progressive reduction in CFR over time may reflect an improvement in the healthcare system's response capacity in terms of early diagnosis, more effective treatments and better organisation of care (Kruk et al., 2020; Elkomy et al., 2024). In this sense, the evolution of the CFR is interpreted as an empirical manifestation of the adaptive resilience of healthcare systems.

However, this indicator must also be interpreted critically, as CFR can be influenced by external factors, such as testing strategies, data quality and reporting practices (Papanicolas et al., 2025); therefore, it is necessary to complement the analysis of the CFR with advanced statistical models capable of capturing the complexity of the relationship between cases and deaths and distinguishing epidemiological effects from organisational and systemic ones. Through this approach, it is possible to interpret the fatality rate not only as a simple descriptive data point but as a useful analytical tool for assessing the degree of resilience of healthcare systems in the long term.

To analyse the effectiveness of resilience over the long term, we rely on the COVID-19 fatality index.

Fatality is an indicator that shows the number of deaths caused by a disease in relation to the number of people infected with that disease (Vladescu, 2004).

Fatality can be calculated based on two measures:

- Infection fatality rate (IFR)
- Case fatality rate (CFR)

IFR is the percentage of deaths among all infected people.

To accurately measure IFR, it is necessary to know the full picture of the number of infections and deaths caused by the disease, including people with mild or asymptomatic symptoms, even if they have not been officially diagnosed. It is calculated as follows:

Infection Fatality Ratio (IFR, 100%) = (number of deaths from disease/number of infected individuals) •100

Since it is impossible to know the actual number of infected individuals, the IFR is an estimate, not a certainty (WHO, 2020) (Matheiu et al., 2020a) (Matheiu et al., 2020b).

The CFR is the percentage of deaths among identified confirmed cases.

The case fatality rate (CFR) is the proportion of people diagnosed with a disease who have died from that disease and is therefore a measure of the severity of the cases detected. It is calculated as follows:
Case fatality Ratio (CFR, 100%) = (number of deaths from disease/number of infected individuals) •100
In post-pandemic data analysis, CFR is considered more reliable because there are no longer error factors such as failure to identify confirmed cases and deaths (WHO, 2020) (Matheiu et al., 2020a) (Matheiu et al., 2020b).

2. Research methodology

The data used in this article comes from the World Health Organization processed by Our World in Data (WHO, 2025a) (WHO, 2025b).
We considered the 46 countries of geographical Europe: Albania, Andorra, Armenia, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova, Monaco, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Russia, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, Ukraine.

Table no. 1. Number of cases and deaths, 2020 - 2024

NATION	TOTAL CASES	TOTAL DEATHS	NATION	TOTAL CASES	TOTAL DEATHS
Albania	337196	3608	**Lithuania**	1419865	9870
Andorra	48015	159	**Luxembourg**	396904	1000
Armenia	454070	8784	**Malta**	123599	926
Austria	6083046	22534	**Moldova**	650874	12283
Belarus	994045	7118	**Monaco**	17181	67
Belgium	4892740	34339	**Montenegro**	251280	2654
Bosnia and Herzegovina	404149	16404	**Netherlands**	8649021	22986
Bulgaria	1338233	38762	**North Macedonia**	352071	9991
Croatia	1353976	18784	**Norway**	1532456	5732
Cyprus	711582	1364	**Poland**	6769693	120976
Czech Republic	4825923	43776	**Portugal**	5670717	29084
Denmark	3445612	10012	**Romania**	3567745	68953
Estonia	613811	3107	**Russia**	24831847	404067
Finland	1508945	11466	**San Marino**	25292	126
France	37989547	161667	**Serbia**	2567962	18057
Germany	37241936	165738	**Slovakia**	1885646	21278
Greece	5755206	39902	**Slovenia**	1362348	9914
Hungary	2237480	49120	**Spain**	13754962	118943

Iceland	210749	186	**Sweden**	2771794	28426
Ireland	1752255	9770	**Switzerland**	4475838	14170
Italy	26959599	198272	**Turkey**	17004712	101419
Kosovo	26713862	3212	**United Kingdom**	25025439	232112
Latvia	977770	7553	**Ukraine**	5541740	109925
Liechtenstein	21613	89			

Source: World Health Organization processed by Our World in Data, 2025.

The data in Table 1 were processed using SPSS 21 software and, in part, Excel.
For this research, we opted for a quantitative approach, as the main objective was to measure the relationship between the number of confirmed COVID-19 cases and the number of deaths reported in different European countries. Quantitative analysis is the most appropriate in this context because it uses official numerical data (cases and deaths) from international sources (World Health Organization, Our World in Data); it allows the application of rigorous statistical methods (regressions, ANOVA, coefficients of determination) that can objectively highlight the existence and intensity of the relationship between variables; it provides replicable and comparable results between countries and time periods, reducing the degree of subjectivity in interpretation.
In this way the quantitative methodology not only confirms or refutes the hypotheses formulated but also allows the impact of health system resilience on mortality to be estimated using concrete and verifiable indicators.

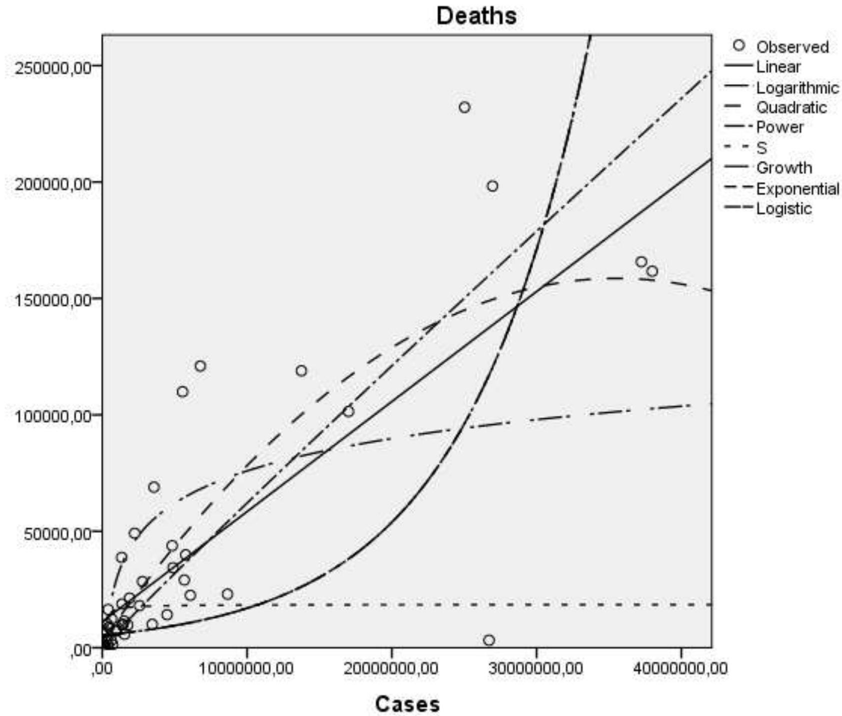

Figure no. 1: SPSS data analysis chart
Source: Author's research

As can be seen from Figure 1, we tested several data analysis methods: linear, logarithmic, quadratic, power, S, growth, exponential and logistic.

To analyze the relationship between the number of cases and the number of deaths associated with COVID-19, three types of statistical models were selected—linear, quadratic (second-degree polynomial), and power—each responding to a different hypothesis regarding the dynamics of the phenomenon:

- the linear model was chosen as a starting point, assuming a direct proportional relationship between cases and deaths. It provides a simple and intuitive first assessment, checking whether mortality increases steadily with the number of confirmed cases.
- the quadratic model (second-degree polynomial) was introduced to capture possible curvilinear relationships, taking into account that the effects of the pandemic do not always manifest themselves proportionally. For example, after exceeding a certain capacity of the healthcare system, mortality may increase more rapidly (acceleration effect) or, conversely, may decrease relatively due to adaptation and improvement of therapeutic strategies.

- the power model was applied because many epidemiological phenomena follow power laws, reflecting increases that are almost proportional but not strictly linear. Through logarithmic transformation, this model allows for the highlighting of diminishing returns or disproportionate effects, providing a more realistic description of the case-death relationship.

3. Results and discussions

The statistical analysis highlights the close relationship between the number of confirmed COVID-19 cases and the number of deaths recorded in different European countries. The main objective was to understand the extent to which the spread of the virus led to deaths and how the resilience of healthcare systems influenced this relationship.

3.1. Linear model

Table no. 2. Anova linear model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	93075801072,673	1	93075801072,673	76,492	,000
Residual	53539169626,631	44	1216799309,696		
Total	146614970699,304	45			

The independent variable is Cases.
Source: Author's research

Table no. 3. Coefficients linear model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Cases	,005	,001	,797	8,746	,000
(Constant)	11212,440	6046,187		1,854	,070

Source: Author's research

Table no. 4. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,797[a]	,635	,627	34882,65055	1,895

Source: Author's research
a. Predictors: (Constant), Cases
b. Dependent Variable: Deaths
R = 0,797 → strong and positive correlation between cases and deaths.
R^2 = 0,635 → approximately 63.5% of the variation in the number of deaths is explained by the variation in the number of cases.
The remaining 36.5% is explained by other factors not included in the model (medical conditions, health infrastructure, demographic factors, etc.).
ANOVA or Fisher's test on the validity of the model tells us that:

Ftable = (1.44) < F calculated = 76.492, $p < 0.001$ → the model is statistically significant.
This means that there is a significant linear relationship between cases and deaths; it is not just a coincidence.

Coefficients:
The constant (intercept) = 11,212.44 is abnormal in this case because even when the number of cases would be zero, the model estimates an average of 11,212 deaths (this may be a statistical effect or related to how the data is recorded).
Coefficient for "Cases" = 0.005 ($p < 0.001$) means that for every 1 new case of COVID-19, the model estimates +0.005 deaths. In other words, for every 1,000 new cases, there are, on average, about 5 deaths.
Standardized beta = 0.797 confirms that the number of cases has a strong influence on the number of deaths.
The model shows that there is a significant and strong linear relationship between the number of COVID-19 cases and deaths, and therefore, as the number of cases increases, so does the number of deaths.
However, we can say that our model explains (based on R^2 - the coefficient of determination) only 63.5% of the variation, so there are other factors at play. The high constant suggests that there are other determinants of mortality (not just reported cases).
The Durbin–Watson statistic tests the autocorrelation of residuals (prediction error) in regression.
Possible values: 0 → 4.
≈ 2 no autocorrelation (residuals are independent).
< 2 significant positive autocorrelation (residuals tend to be linked).
> 2 significant negative autocorrelation.
In this case, DW = 1.895, very close to 2, which suggests that there are no major problems with autocorrelation of the residuals. This means that the regression model is "cleaner" and the predictions are not systematically affected by correlated errors.

3.2. Quadratic model

Table no. 5. Anova quadratic model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	98728229327,254	2	49364114663,627	44,327	,000
Residual	47886741372,050	43	1113645148,187		
Total	146614970699,304	45			

The independent variable is Cases.
Source: Author's research

Table no. 6. Coefficients of the quadratic model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Cases	,009	,002	1,479	4,694	,000

Cases ** 2	-1,234E-010	,000	-,710	.	.
(Constant)	2878,333	6865,992		,419	,677

Source: Author's research

3.2. Power model

The Power regression model (or "power" model) differs from the linear model in that it assumes that the relationship between the dependent variable (Y – in this case, deaths) and the independent variable (X – cases) follows a power function:

$$Y=a \cdot X^b$$

where:

a = scaling coefficient (the intercept, but expressed in a different form),

b = the exponent that shows how Y varies relative to X.

Features of the Power model:

- nonlinear relationship. Unlike linear regression (where increases in X lead to constant increases in Y), in the Power model:
  - if $b > 1 \rightarrow$ the increase in Y is accelerated (explosive effect).
  - if $0 < b < 1 \rightarrow$ Y increases more slowly than X (diminishing returns effect).
  - if $b < 0 \rightarrow$ inverse relationship (as X increases, Y decreases).
- logarithmic transformation for estimation. The model can be linearized as follows:

  $$\ln(Y)=\ln(a)+b \cdot \ln(X)$$

  Then a linear regression between log(Y) and log(X) can be applied to estimate the parameters.

Practical interpretation. If the Power model is correct, the case-death relationship would show that the number of deaths increases disproportionately to cases, depending on the value of the exponent. This type of model is often used when effects amplify or reduce depending on the magnitude of the phenomenon (epidemics, economic growth, ecology).

Table no. 7. Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
,884	,781	,776	,990

Source: Author's research

Table no. 8. Anova Power model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	154,100	1	154,100	157,178	,000
Residual	43,138	44	,980		
Total	197,239	45			

The independent variable is Cases.

Source: Author's research

Table no. 9. Coefficients Power model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		

ln(Cases)	,963	,077	,884	12,537	,000
(Constant)	,011	,013		,904	,371

The dependent variable is ln(Deaths).
Source: Author's research

Model Summary Interpretation
R = 0.884 indicates a very strong correlation between the number of cases and deaths (after logarithmic transformation).
R^2 = 0.781 shows that approximately 78.1% of the variation in the number of deaths is explained by the variation in the number of cases (more than in the linear model, where it was 63.5%).
Therefore, the Power Model better describes the relationship than the linear (63.5%) or quadratic (67.30%) models.
We test the validity of the model with ANOVA:
F= (1.44) < calculated F= 157.178, $p < 0.001$ → the model is statistically significant.
This means that the “cases” variable explains an essential part of the variation in deaths.
The model was estimated based on the logarithmic form:

$$\text{Ln (Deaths)} = 0.011 + 0.963 \ln \text{(Cases)}$$

Transforming back:

$$\text{Deaths} \approx e^{0,011} \cdot (\text{Cases})^{0,963}$$

Which is:

$$\text{Deaths} \approx 1,011 \cdot (\text{Cases})^{0,963}$$

Exponent b = 0.963 ($p < 0.001$) → deaths increase almost proportionally to the number of cases, but slightly slower (sub-proportional, because b < 1).
Constant a ≈ 1.011 → scaling factor very close to 1.
Practical interpretation
If the number of cases doubles, the number of deaths increases by almost 2 times, but slightly slower (because the exponent is < 1).
Compared to the linear model:
The Power model provides a better fit (higher R^2).
It describes an epidemiological relationship more realistically (where growth is not strictly linear, but with diminishing returns).

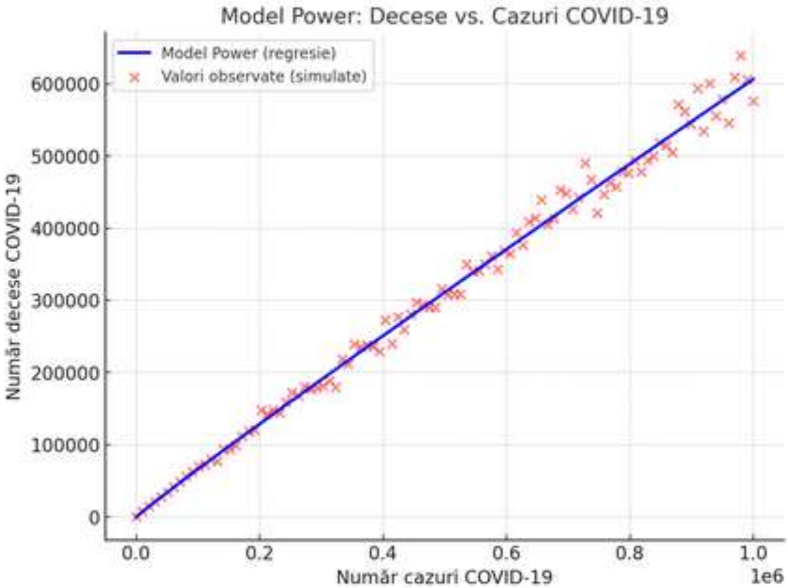

Figure no. 2: Model Power
Source: Author's research

3.3. Evolution of the CFR

In order to assess the resilience of healthcare systems during the pandemic years (2020–2024), we also analysed the evolution of cases, deaths and CFR over time.

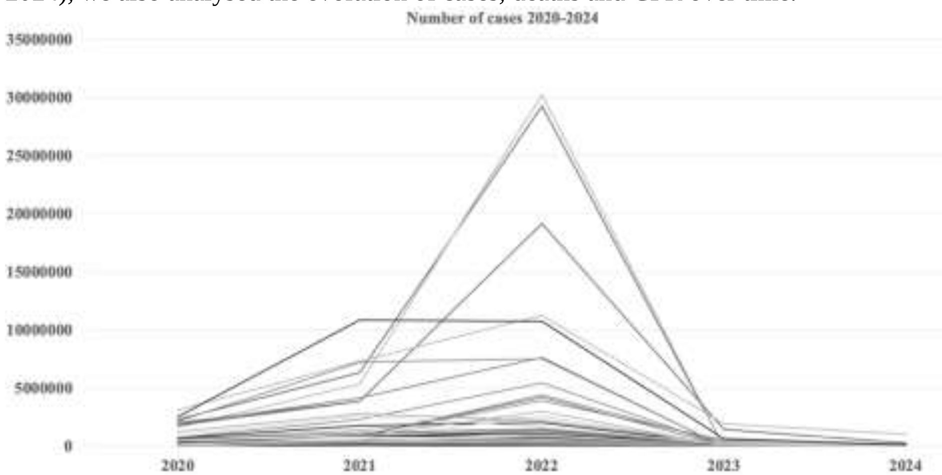

Figure no. 3: Number of cases 2020-2024
Source: Author's research

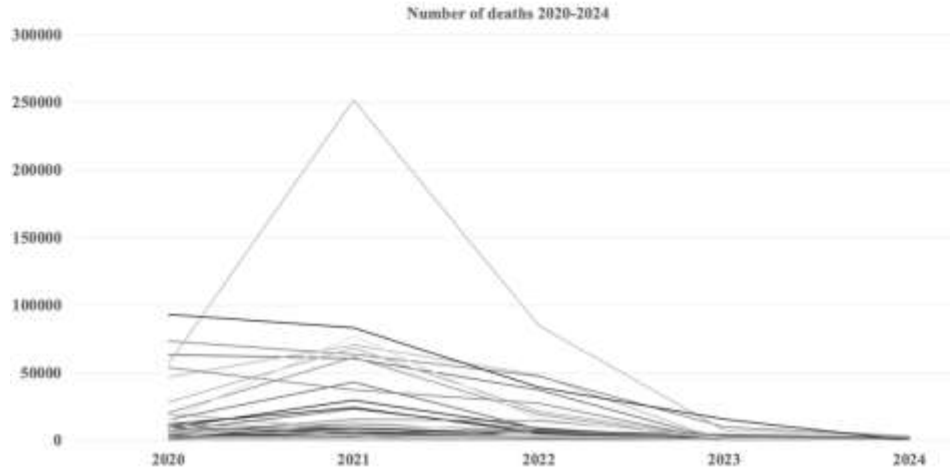

Figure no. 4: Number of deaths 2020-2024

Source: Author's research

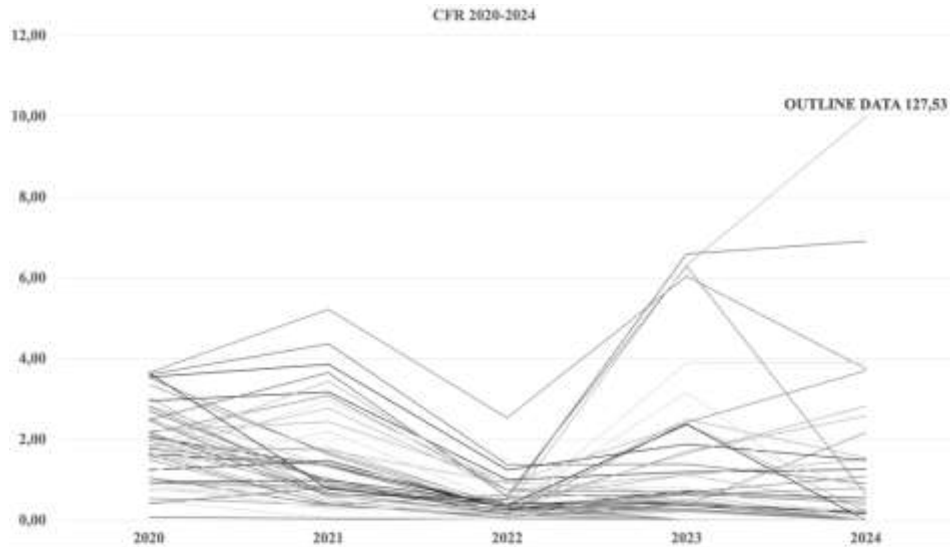

Figure no. 5: Cases Fatality Ratio (%) 2020-2024

Source: Author's research

Analysis of the trend in the Case Fatality Ratio (CFR) in the period 2020–2024 provides an indirect insight into the level of resilience of European health systems. In the early years of the pandemic (2020–2021), the CFR recorded high values, reflecting the extreme pressure on systems, the lack of established treatment protocols, and the shortage of medical devices and adequately trained personnel. At this stage, resilience was low because systems reacted mainly reactively and with limited resources.

From 2022 onwards, with increased organisational capacity, the introduction of vaccines, the roll-out of new therapies and the adaptation of healthcare facilities, the CFR began to decline significantly. This decline reflects an improvement in resilience, understood as the ability to learn, adapt and absorb shocks. In practice, with the same number of infections, the proportion of deaths has decreased, a sign that systems were able to provide more effective and timely care.
However, the CFR must be interpreted with caution, as anomalous values may result from detection problems rather than a real change in resilience. One example is Latvia in 2024, where the "outline data" shows a very high CFR (over 120%). This data does not indicate a sudden fragility of the system, but rather a significant reduction in testing activity: with fewer swabs carried out, the number of cases is artificially low, while deaths, being more difficult to conceal, remain high. The result is a distorted CFR, which paradoxically exceeds 100%.
In summary, the CFR graph not only describes the epidemiological trend, but also becomes an indirect measure of healthcare resilience:

- high and stable CFR → limited resilience (difficulty in responding, system overload).
- decreasing CFR → increasing resilience (organisational adaptation, improvement in clinical practices, better use of resources).
- abnormal CFR → critical issues in surveillance systems (incomplete data, reduced testing, lack of transparency).

This perspective confirms that resilience is not an abstract concept, but a factor that can be observed and measured through the evolution of epidemiological indicators, provided that the quality of the data collected is high and consistent over time.

3.4. Results

The initial linear regression model showed that as the number of cases increases, the number of deaths also increases significantly. The correlation coefficient ($R = 0.797$) indicates a strong and positive relationship, while the coefficient of determination ($R^2 = 0.635$) reveals that approximately two-thirds of the variation in the number of deaths can be explained by the trend in cases. However, a substantial margin (36.5%) remains attributable to other factors, such as demographic characteristics, the pre-existing health status of the population, the capacity of healthcare facilities, or the effectiveness of emergency management policies.
The linear model, therefore, confirms that there is a clear link between cases and deaths, but also suggests the presence of latent variables that deserve attention, such as the quality of intensive care or the speed of implementation of isolation measures.
The quadratic model attempted to capture any more complex dynamics, given that the relationship between infections and mortality is not always perfectly proportional. This model slightly improved explanatory power compared to the linear model, but did not provide the most accurate representation of reality.
The most interesting result comes from the Power model, based on a logarithmic transformation of the data. Here, the correlation coefficient reaches even higher values ($R = 0.884$), and R^2 increases to 78.1%, indicating that almost 80% of the variations in deaths can be attributed to the number of cases. This means that this approach better

describes the phenomenon, providing a more realistic picture of the epidemiological dynamics: deaths increase almost proportionally to cases, but with a slightly more moderate increase. In practical terms, if cases double, deaths also increase significantly, but not in a perfectly proportional manner.
This evidence is particularly important because it shows that, even in the presence of high infection rates, the healthcare system's ability to adapt and respond can mitigate the impact on mortality. Resilience, therefore, translates into a reduction in the case fatality rate (CFR), as confirmed by the trend over time: in 2021, the year with the highest pressure on the system, the CFR reached its highest levels, while in 2022, with the strengthening of organizational and therapeutic capacity, it fell significantly.
In conclusion, the data suggest that the resilience of the healthcare system is not just a theoretical concept, but a measurable factor that directly affects the outcomes of the pandemic. Where resilience was higher, mortality rates were lower, while in more fragile contexts, the impact of the virus was more severe.

Conclusions

One factor that cannot be overlooked during the COVID-19 pandemic is the variability in case and death estimates. A general comparison between European countries is difficult for several reasons. Some countries have been reluctant to identify and report all deaths caused by COVID-19. Different countries have used different case definitions and testing strategies or counted cases differently (e.g., without testing or counting mild cases). Differences in response, or resilience, such as the implementation of treatments or interventions introduced at different stages of the disease, may also play an important role, but vaccination campaigns and their implementation have also had an impact. Finally, patient profiles (e.g., age, sex, ethnicity, and underlying comorbidities) may vary from country to country.
The analysis confirms that the resilience of healthcare systems was a determining factor in mitigating the impact of the COVID-19 pandemic in Europe.
In the early stages of the pandemic, healthcare systems showed clear signs of fragility: high mortality rates reflected poor preparedness, limited availability of resources, and delays in adopting effective treatment protocols. Over time, however, resilience has gradually improved, as evidenced by the reduction in the case fatality rate (CFR). We can assume that several factors have contributed to this process: the rapid rollout of vaccination campaigns, the reorganization of hospital services, the introduction of new therapies, and greater institutional capacity to coordinate the healthcare response.
The statistical models applied, in particular the power model, have shown that deaths have increased almost proportionally to cases, but resilience mechanisms have helped to mitigate this relationship, avoiding a purely linear escalation. This confirms that resilience is not an abstract concept, but a measurable element with concrete effects on mortality reduction.
Three main lessons emerge from the analysis:

- institutionalize resilience: resilience must be integrated into long-term health planning through clear governance mechanisms, sustainable financing, and systematic emergency preparedness checks.

- strengthen adaptability: flexibility in clinical protocols, rapid mobilization of resources, and continuous learning processes have proven to be key elements in reducing mortality.
- invest in equity and prevention: resilience is only truly effective if it includes vulnerable populations and reduces inequalities in access to care, vaccination, and information.

In conclusion, the COVID-19 crisis has shown that resilience is a strategic necessity for health systems and not an optional extra. Where resilience was greatest, the impact of the pandemic was limited; where it was lacking, fragilities translated into higher mortality rates. Learning from these lessons will be key to strengthening preparedness and ensuring that Europe is better equipped to deal with future health emergencies.

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