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An Investigation of the Impact of Anti-Epidemic Measures and Non-Pharmaceutical Interventions on Mitigating the Spread of the COVID-19 Pandemic

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Abstract: COVID-19, caused by the SARS-CoV-2 virus, was first identified in December 2019 and rapidly evolved into a global pandemic. Although much of the research has focused on predictive models, less attention has been given to analyzing the effectiveness of anti-pandemic measures before the availability of vaccines. This study aims to fill that gap by analyzing the correlation between key COVID-19 endpoints—new confirmed cases and new deaths—across five countries: Italy, France, Germany, the United Kingdom, and the United States. We use a broad range of data sources, including population demographics, geography, health indicators, government responses, mobility patterns, and traffic data, all spanning from March 2020 to April 2021. The dataset covers three waves of the pandemic, with the third wave influenced by the early availability and distribution of vaccines. To identify the most significant factors, a feature selection process was applied to the data, helping to determine the key measures influencing the pandemic's course. Our findings contribute valuable insights for future pandemics, providing policymakers with evidence-based guidance for implementing the most effective anti-pandemic measures when vaccines are not yet available.

Keywords: correlation analysis; non-pharmaceutical measures; healthcare infrastructure; government response; confirmed and death cases; dweller mobility

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1. Introduction and Literature Review

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is the virus that causes COVID-19 (coronavirus disease 2019), the respiratory illness responsible for the COVID-19 pandemic [1]. It is unusual viral pneumonia in patients, first found in late December 2019. In a few months, the World Health Organization declared a pandemic because of its fatal effects on public health [2]. The process of authorization of the first vaccines began in late 2020 while their distribution started in and continued throughout 2021. Before vaccines became widely available, public health authorities and governments around the world relied on a combination of non-pharmaceutical interventions and strategies. Which were the most effective measures to mitigate the spread of the pandemic? Obviously, these measures were effective to varying degrees in different countries depending on the timing of implementation [3].

The literature contains hundreds of studies on COVID-19 published from the beginning of 2020 to date. Research on the immunology of coronavirus, clinical and therapeutic approaches, on the evolution of coronavirus and transmission, the vaccine production and distribution, the associated psychological disorders, material science and engineering challenges, public health, and emergency management has been published to tackle the pandemic and mitigate its impact.

One critical area of research focuses on predicting COVID-19 and measuring correlations between confirmed cases (and deaths) and various controlled and uncontrolled factors, such as government decisions, community mobility measures, demographics, and hospitalizations. Statistical analyses and machine learning techniques provide effective models and tools for mining correlations between different health indicators, emergency decisions, and pandemic evolution [4]. The availability of freely available statistical toolbox further encourages exploring interventions strategies to mitigate the pandemic's impact [5,6].

Several literature contributions have presented correlation analyses [7–11] applied to COVID-19 data before the distribution of vaccines. These analyses involve different patterns and multiple countries for comparison. For example, Ref. [12] used the Pearson coefficient to measure the correlation between the stock market and COVID-19, while Ref. [9] used the Spearman and Kendall coefficients to group countries with similar correlation measures. Ref. [7] used the cross-correlation technique to estimate the relationship between human mobility patterns and COVID-19 daily cases in Jakarta and Indonesia. Additionally, Ref. [13] presented a literature review on human mobility behavior in the context of the current pandemic.

Researchers in [14] developed a tool to monitor diseases and analyze the spatiotemporal epidemiology of SARSCoV-2. Another significant contribution was made by [11], who conducted a correlation analysis on climate indicators using New York pandemic data. Additionally, Ref. [15] investigated the spatial–temporal variations in COVID-19 occurrences in relation to climate fluctuations. Furthermore, Ref. [10] selected a limited set of independent critical factors such as population density, elderly population, ethnic minority populations, diabetics, income, and smoking adults to measure their correlation with COVID-19 occurrence. This involved the quantification of Pearson's correlation and a spatial–geographical analysis covering the United States.

Feature selection analysis is crucial for understanding the dynamics of phenomena such as the COVID-19 pandemic. One commonly used approach is the Principal Component Analysis (PCA) method, which is frequently employed in COVID-19 investigations [16–18]. However, PCA is not suitable when dealing with both categorical and continuous features simultaneously.

The literature showcases several contributions that demonstrate the purpose and scope of "feature ranking analysis". Such contributions also compare different models and algorithms used to measure the relevance of a specific attribute to a target response, such as a selected endpoint [19,20]. Further details about the chosen algorithm for this study are discussed in Section 5.

The correlation analysis and the feature selection are usually the first steps towards a prediction study. Some scientific papers have presented predictive studies using techniques such as time series smoothing, neural networks, and random forest [2,8,21–24]. However, these studies were often conducted on specific countries and limited to the first wave of the COVID-19 disease. For instance, one study [24] forecasted epidemiological trends of the COVID-19 pandemic for 16 countries, including the USA, Brazil, India, Mexico, South Africa, and Italy. More recent studies have focused on subsequent waves of COVID-19 and the mass distribution of vaccines [4,25,26]. These studies have utilized time-series analyses, auto-regression techniques, Monte Carlo agent-based modeling [25], diffusion modeling [27], artificial neural network modeling [26], and the SIR compartmental model [28]. Additionally, there are explicit models that estimate the total number of deaths and the cumulative number of deaths due to the COVID-19 virus in the United States [29]. Furthermore, Ref. [30] estimated the COVID-19 death toll, considering the time-dependent effects of pandemic restrictions and changes related to COVID-19 in various regions and cities in the United States.

Along with the global pandemic spread, the role of vaccines in tackling epidemic waves is assessed in different countries. Ref. [31] mined citizens' willingness or reluctance to be vaccinated in seven European countries. The dynamics of the pre- and post-vaccine waves in Rio de Janeiro city using techniques such as the Poincaré plot, approximate entropy, second-order difference plot, and central tendency measures are illustrated in [32]. Manjarrez et al. [33] employed Fourier and similarity analyses to examine mortality patterns within the frequency domain. By using a composite pandemic severity index and hierarchical clustering and by subdividing the pandemic into fifteen phases, Ref. [34] identified similar trajectories of pandemic severity among all German counties.

Major interest is paid to citizens' behavioral and habits change during and after COVID-19 in different countries. Kinoshita et al. [35] investigated the discrepancy between infection prevention intentions and citizen behaviors using Bayesian probability revision. Perceived risk and psychological factors in response to the pandemic's waves are also correlated with the citizens' retail shopping abandonment in [36]. The shift to alternative transportation modes in urban and long-range mobility is explored in light of the spread of the pandemics and the perceived risk [37–39], but not enough investigated as an anti-epidemic lever of intervention. In addition to studies on individual behavior, research has also focused on the effectiveness of government-imposed restrictions in controlling the pandemic's spread. Apio et al. [40] used the stringency index to evaluate the level of restriction policies in Korea, proposing a more country-specific measure, the Korea stringency index (KSI), to capture the nuanced impact of these policies. Similarly, Kishore et al. [41] utilized the Oxford stringency index (SI) across multiple countries to assess how government responses correlated with the severity of COVID-19 outcomes, further reinforcing the critical role of policy measures in pandemic control. These studies complement the investigation of behavioral changes by demonstrating the direct influence of government restrictions on population mobility and pandemic progression.

To the authors' knowledge, no studies have already correlated the pre-vaccine evolution of COVID-19 across waves in different countries, with controlled and uncontrolled features belonging to a multitude of domains. These domains include both controlled features influenced by government responses and decisions (such as school closures, restrictions on community mobility and transportation, workplace closures, and facial covering) and exogenous uncontrolled features (such as geographical indicators, population demographics, or citizens behavior).

This paper aims to measure the correlation between a large number of features monitored daily for significant countries to analyze pre-vaccine government strategies and decisions and their ranked effectiveness against new confirmed COVID-19 cases (1) and deaths (2). We refer to (1) and (2) as responses and endpoints of this study. A comparative study to measure the effects of demographic, geographic, and healthcare system factors, with different anti-pandemic restrictions to citizens' mobility and social places for different countries before the spread of vaccines has not been conducted yet and is hence mandatory to prepare for new COVID-19-like pandemics in the future.

The subsequent sections of this paper are structured as follows: Section 2 introduces the proposed methodology for data collection, database construction, and correlation analysis comparing different periods and countries. Section 3 outlines the selected data sources for the database construction, presenting the features involved in the correlation analyses with confirmed cases and new death cases. Section 4 presents the results of the correlation analyses and discusses significant findings from a comparative study of correlation measures for different countries and periods. Section 5 demonstrates a feature ranking analysis to identify the most relevant features. Finally, Section 6 delivers a conclusive discussion encompassing conclusions and areas of interest for further research.

2. Methodology

The outlined methodology comprises four primary steps, database building (1), data entry (2), correlation analysis (3), and feature ranking and selection (4), involving a critical analysis of the attributes relevant to this study.

This methodology is characteristic of many data mining and machine learning analyses conducted on extensive datasets. Specifically, the COVID-19 pandemic has facilitated the accumulation of numerous records, each representing a country under analysis. These records encompass a range of features, both categorical and non-categorical, sourced from diverse origins. Regrettably, some records are incomplete for certain countries due to the absence of at least one feature. Consequently, the focus has been directed towards countries with complete data and "comparable countries" such as Italy, France, Germany, the UK, and the United States. The initial subset pertains to the European community, while the inclusion of the UK and the US enables substantial comparative analyses, which are pivotal for this study and its subsequent discussion.

3. Database Building

The following section outlines the database architecture established for the correlation analysis component of this study. It is a dynamic, time-based database that aggregates records from various open-database sources across the globe, encompassing data from numerous countries. The primary sources were carefully selected based on their high level of availability, daily updates, and global reach, ensuring the most current and consistent data for analysis. These primary sources encompass the following:

- GitHub, which is a provider of Internet hosting for software development (https://github.com/, accessed on 1 November 2021);
- Eurocontrol, which is a pan-European civil military organization dedicated to supporting European aviation (https://www.eurocontrol.int/, accessed on 1 November 2021);
- Oxford government responses (https://covidtracker.bsg.ox.ac.uk, accessed on 1 November 2021);
- Apple mobility trends (https://covid19.apple.com/mobility, accessed on 1 November 2021), available upon request;
- Epidemiology open data, community mobility open data (https://ourworldindata.org/covid-google-mobility-trends, accessed on 1 November 2021);
- Geography, healthcare system, and demographics data.

Table 1 presents the detailed list of open sources selected for the database construction and daily record fulfillment. A brief description and the URL gives the reader more detailed info and a direct link to collect and update new data.

The data sources at our disposal can be categorized as "static" and "dynamic" datasets. Figure 1 exemplifies the merging process of the datasets, including geography, demographics, and health-related indicators. We make a clear distinction between time-dependent feature sets and time-invariant feature sets. The former pertains to the epidemiology waves, government restrictions, and their consequential impacts on the mobility of inhabitants. The latter elucidates the geographical, demographical, and infrastructural attributes of the countries under observation. Our specific focus lies in the healthcare system, encompassing factors such as life expectancy, the number of hospital beds, and the availability of nursing staff, among others.

Table 1. Selected sources for data collection.

Data Source Typology	URL (All Accessed on 1 November 2021)
Population demographics	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-demographics.md
Geography	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-geography.md
Health related indicators	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-health.md
Oxford COVID-19 government response	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-government-response.md
Google COVID-19 community mobility	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-mobility.md
Apple COVID-19 community mobility	https://github.com/ActiveConclusion/COVID19_mobility
Air traffic data	https://ansperformance.eu/reference/dataset/airport-traffic/
Hospitalizations, patients of COVID-19 and hospitals	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-hospitalizations.md
Epidemiology, COVID-19 infections	https://github.com/GoogleCloudPlatform/covid-19-open-data/blob/main/docs/table-epidemiology.md

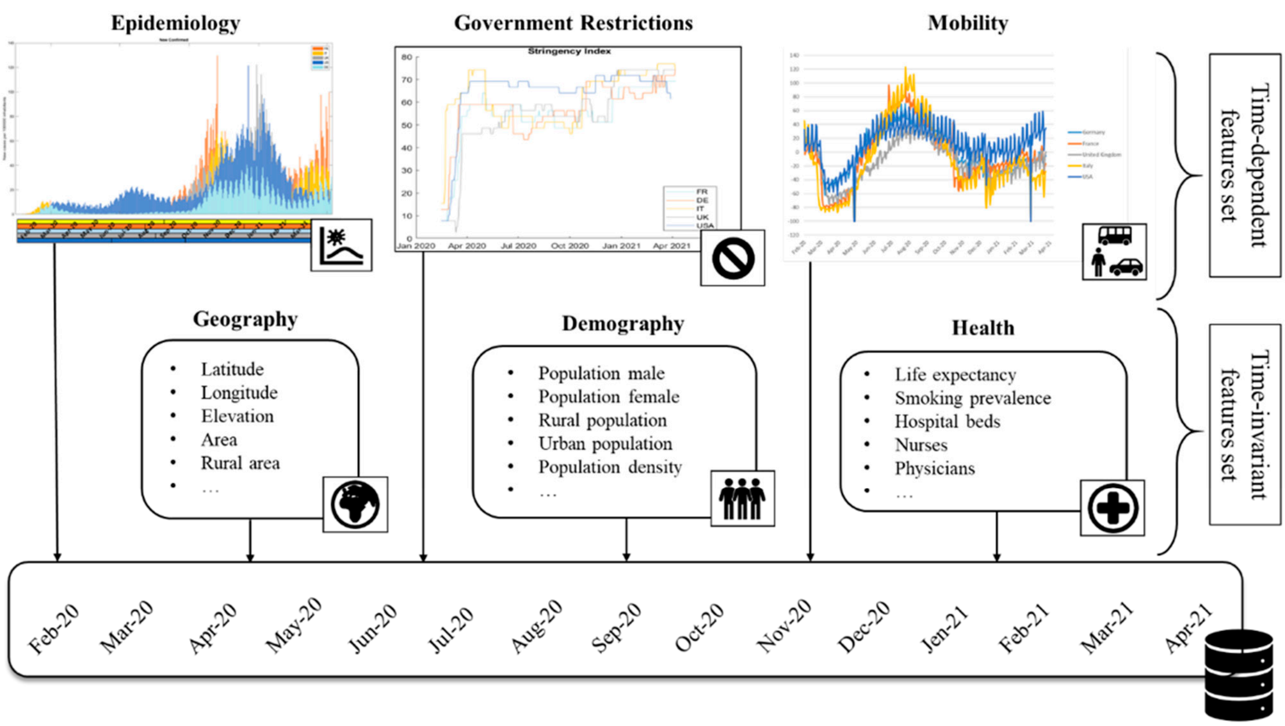


Figure 1. Merging process from different data sources.

Appendix A presents a detailed description of the database structure and features.

In the context of a given country, the term "wave" denotes the period of a pandemic disease characterized by a substantial increase in new cases, followed by a subsequent decrease or stabilization. Table 2 provides a comprehensive account of these periods for the specific set of countries under scrutiny for correlation and comparative analysis, as delineated in the subsequent sections.

Table 2. Waves, starting and ending times, for the selected countries in March 2020–April 2021.

Country	First Wave	Second Wave	Third Wave
Italy	15 February 2020–14 August 2020	15 August 2020–7 February 2021	8 February 2021...
France	15 February 2020–28 July 2020	29 July 2020–10 December 2020	11 December 2020...
Germany	15 February 2020–31 July 2020	1 August 2020–20 February 2021	21 February 2021...
UK	15 February 2020–14 August 2020	15 August 2020–30 November 2020	1 December 2020...
USA	15 February 2020–9 June 2020	10 June 2020–27 September 2020	28 September 2020...

4. Correlation Analysis

The objective is to assess the degree of correlation between two critical target responses: the new confirmed cases and the new deaths, and the detailed features outlined in Appendix A. Figure 2 illustrates the trajectory of the new confirmed cases and the new deaths for the selected countries during the specified time period (February 2020–April 2021).

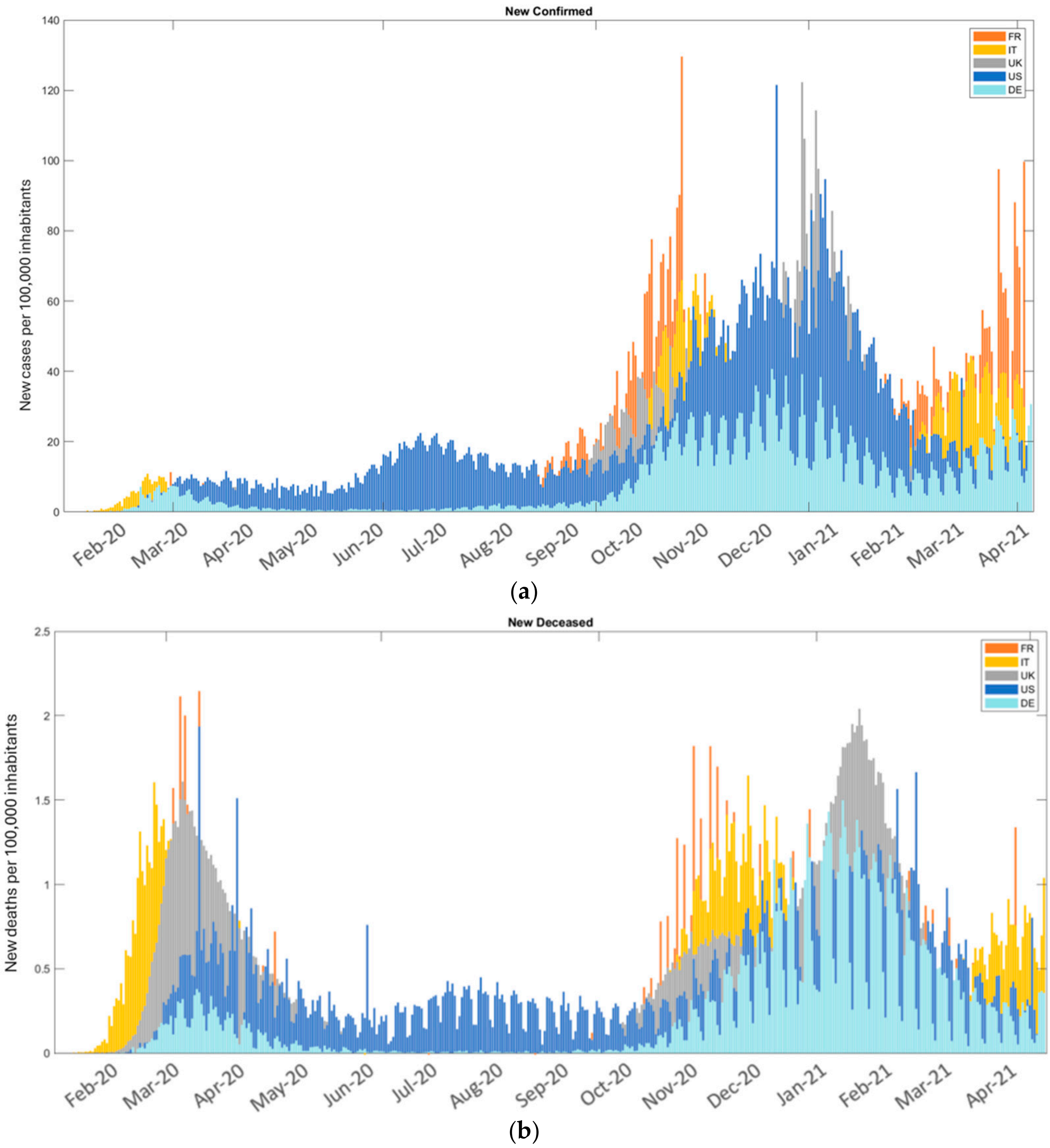


Figure 2. New confirmed cases (**a**) and new deaths (**b**) from February 2020 to April 2021.

Figure 3 (stringency index) and Figure 4 (mobility features) depict the trend of the features for the specified period and the cohort of countries under study. It is important to note that decisions regarding government restrictions vary across countries and over time.

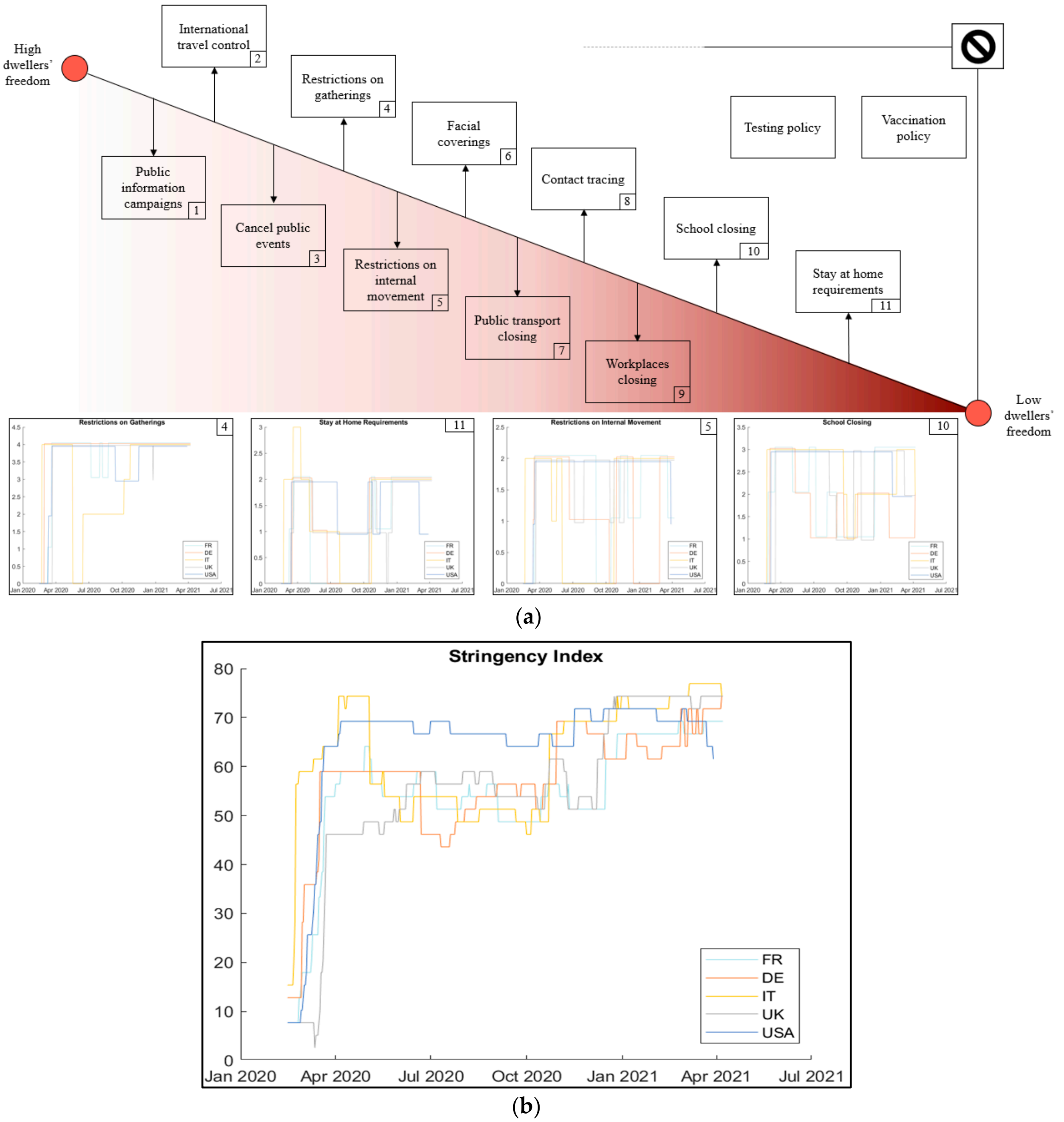


Figure 3. Oxford COVID-19 government responses (**a**) and stringency index (**b**).

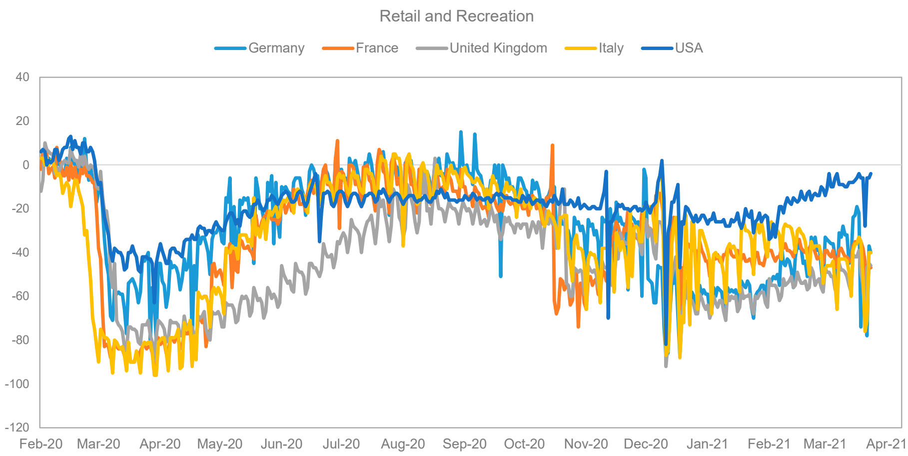
The COVID-19 stringency index [42] is monitored daily for each country and reflects the level of government mobility restrictions in response to the pandemic. It consolidates various policy measures, such as lockdowns, travel restrictions, and social distancing, into a single composite score. The index is standardized to a scale from 0 to 100, where higher values indicate stricter government interventions, leading to closures and limitations on mobility. This index highlights the variability in restrictions not only across countries but also over time. It primarily captures the government's actions, rather than the behavior or impact on specific population groups.

Appendices B and C reports the Spearman correlation values between two selected endpoints and the categorical and continuous features used in this study. The Spearman correlation is suitable for analyzing both continuous and categorical variables. To quickly identify a specific correlation measure, a naming convention based on three variables has been introduced: "endpoint_feature_country_wave".

For example, if we consider the feature "school closing" (refer to Appendix B) and the endpoint "new confirmed cases," the global correlation index across all countries is also provided (highlighted in bold in Appendices B and C). For the first wave, the value is 2.717; for the second wave, it is 0.152; and for the third wave, it is 1.02. It is important to note that the correlation at the individual country level can significantly differ from the global correlation, providing additional insights for analysts.

Some correlation values may be absent in the tables because the related feature is constant for the selected records. For instance, the correlation level for "new cases_school closing_Germany_3rd wave" may be missing if the related feature is constant.

Section 4.1 illustrates some results of the correlation analysis conducted on the new confirmed cases (Sections 4.1.1 and 4.1.2) and the new deaths (Section 4.1.3).



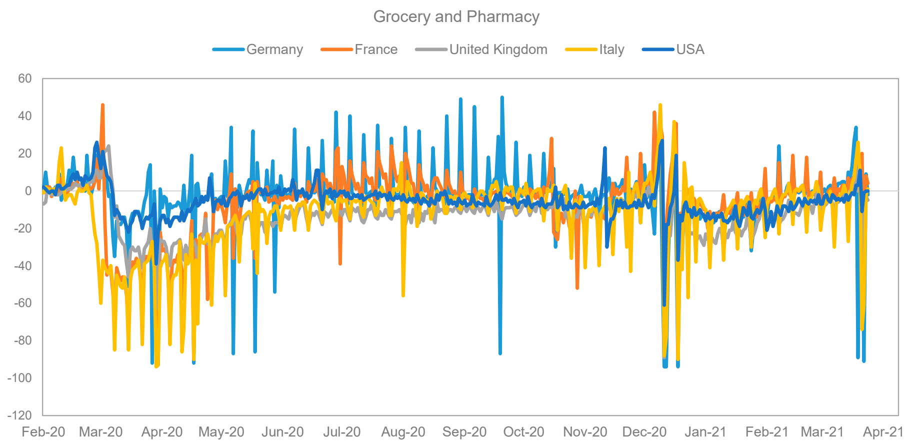
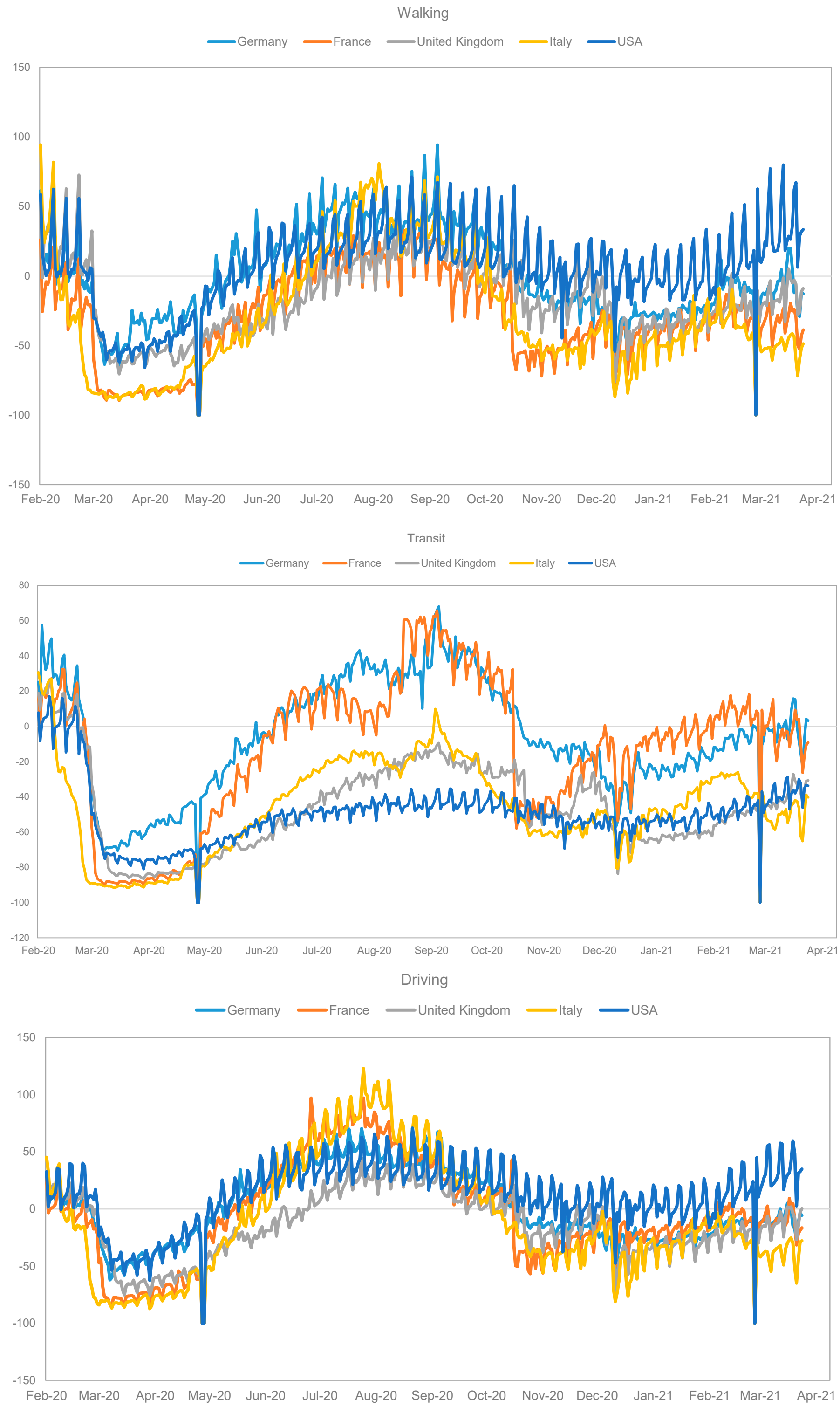


Figure 4. *Cont.*

(**a**) Retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, residential.

Figure 4. *Cont*.



(**b**) Walking, transit, driving.

Figure 4. Feature trend. Google COVID-19 Community Mobility (**a**) and Apple COVID-19 Community Mobility (**b**).

4.1. Oxford Government Responses and Citizens' Mobility Features

4.1.1. Oxford Government Responses—New Confirmed Cases

The correlation analyses were conducted on the new confirmed cases and the Oxford government responses (Appendix B, table (a)). The stringency index levels of correlation are notably high, particularly during the first wave, with a global value for the new confirmed cases at 2.524. The overall level quantified across the three time periods (from first to third wave) is 5.807. This generic global value has been denoted as the "score" of the selected feature. In the UK, the three levels of correlation quantified for the stringency index are close to 0 (−0.014 in the first wave, −0.126 in the second, and −0.093 in the third). The highest values are observed in the first wave (0.769 in Italy). The trend of the stringency index and its individual contributions are detailed in Figure 3. Other significant and high levels of correlation pertain to the following features:

- Stay at home requirements (score 6.518, which is the sum of the three waves' values; 3.658 global level in the first wave; 0.878 for the USA in the first wave).
- Workplaces closing (score 5.22, which is the sum of the three waves' values; 3.251 global level in the first wave; 0.903 for the UK in the first wave).
- School closing (score 3.889, which is the sum of the three waves' values; 2.717 global level in the first wave; 0.637 for Germany in the first wave).
- Restriction on gatherings (2.925 global level in the first wave).

Contact tracing correlation values generate the global score of −1.57, which refers to the first wave period. This score is one of the negative correlation values recorded in the correlation level table of the Oxford government responses.

4.1.2. Citizens' Mobility Features—New Confirmed Cases

The analysis presents the following findings from the correlation analyses involving mobility features and new confirmed cases (Appendix C, table (a)):

- The correlations exhibit high levels, with the global score for the residential feature reaching 7.991, and often being lower than zero. Notably, the global score for the retail and recreation feature stands at −6.796, with a peak in the first wave for the UK.
- The residential feature correlation is predominantly positive for each country and all three time periods, except for France in the third wave (−0.136), suggesting a divergent governmental strategy.
- Traffic data also demonstrate high levels of negative correlations.

The continuous new deceased feature correlation levels closely approach 1 (peaking at 0.914 for the UK in the first wave), signifying a notable correlation between new deaths and new confirmed cases, particularly in the first and second waves (with a global score of 4.015 in the first and 3.579 in the second). This correlation notably decreases from the first to the third wave (global score 1.688).

4.1.3. Citizens' Mobility Features—New Deaths

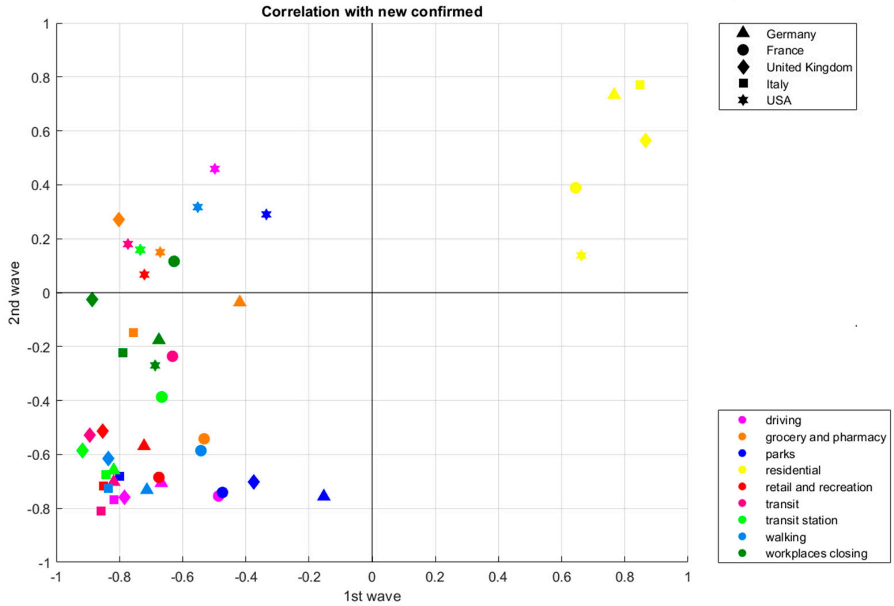
The following are some findings from the correlation analyses conducted for the endpoint new deaths (Appendix C, table (b)):

- Oxford government response features: The highest global score level of correlation is 6.85 for the stay-at-home requirement feature (UK and France have levels higher than 0.85 in the first wave). The Spearman level is 6.691 for the workplaces closing feature (the peak is in the UK's first wave, equal to 0.887).
- The level of correlations with the mobility features are notably high. For instance, the global score for the parks feature is −7.177, for transit stations −8.466, and for residential 9.737 (0.912 for Italy in the first wave).
- The level of correlation with the new confirmed cases feature is also very high.

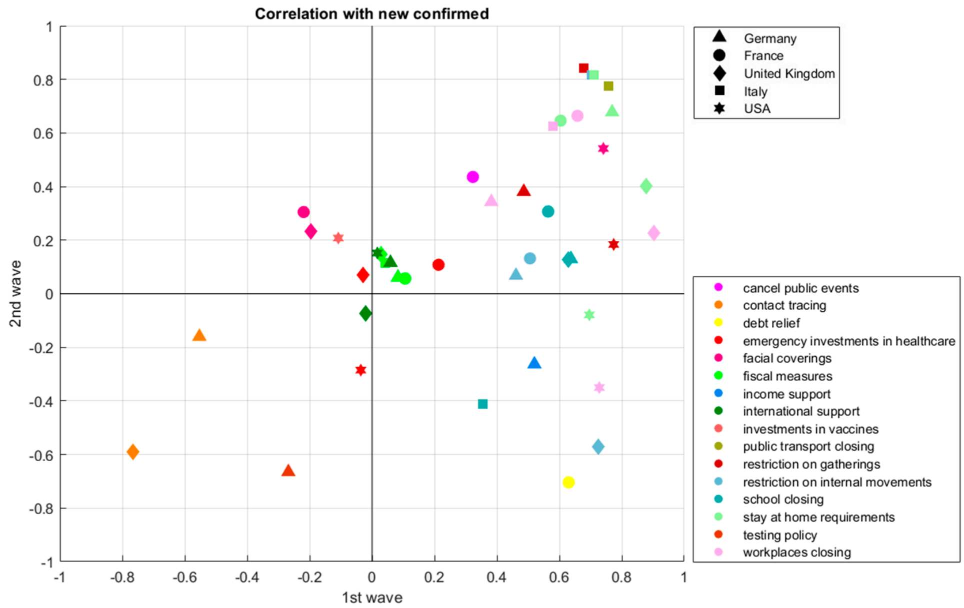
Further discussion regarding the analysis and comparison of the correlation levels assumed in different periods and for other countries can be found in the following two subsections: the first devoted to the "new confirmed cases" and the second to the "new deaths" endpoint.

4.2. New Confirmed Cases—Comparative Analysis

The dot plots showcased in Figures 5 and 6 illustrate the results of correlation analyses conducted across different time periods, specifically comparing the first wave vs. second wave and second wave vs. third wave for selected countries. The horizontal axis of the plot denotes the correlation levels quantified during specific wave periods. Each dot on the plot represents a specific country, with the color indicating a particular feature. Dots of the same color in close proximity means that the countries adopted similar strategies for that feature in the two consecutive periods, even if such strategies differed between the first and second periods.



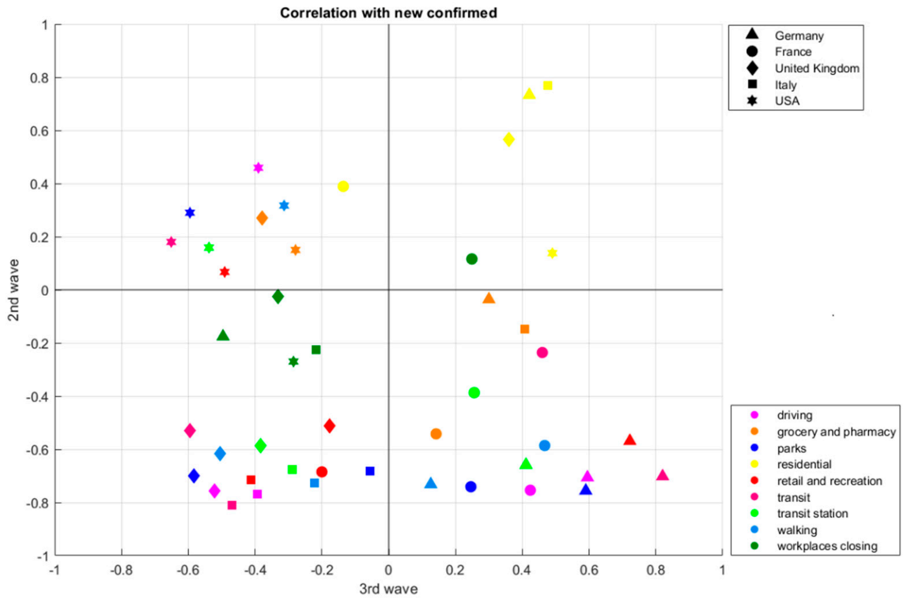
(**a**) mobility features



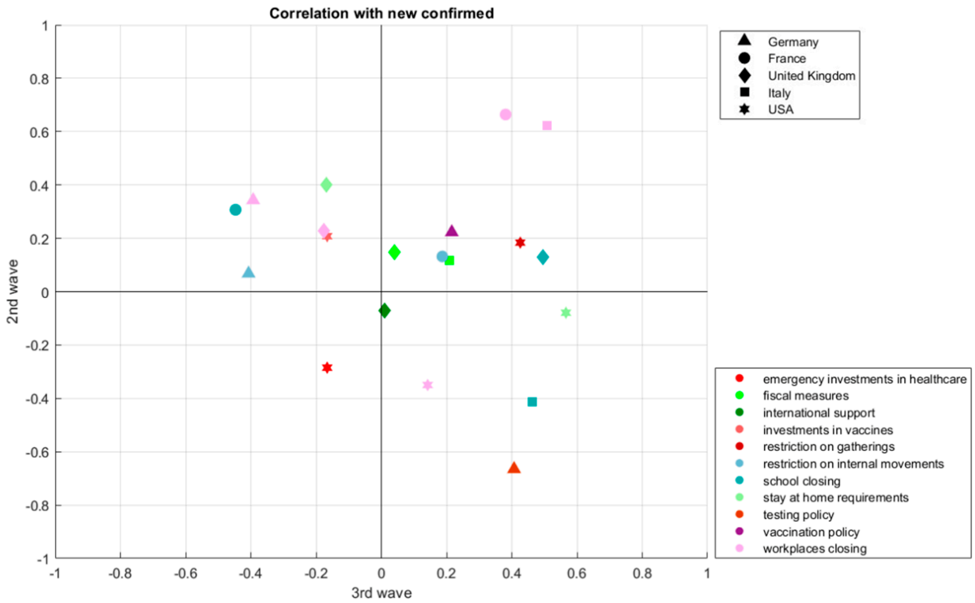
(**b**) Oxford features

Figure 5. Correlation analysis—endpoint "new cases", 1st wave vs. 2nd wave: (**a**) "mobility" features; (**b**) "Oxford" features. Matlab toolbox.

Furthermore, Appendices B and C highlights the absence of certain correlation values for specific countries, variable pairs (one feature and one endpoint), and a given wave period. This indicates that the Spearman correlation measure cannot be calculated. Consequently, the disappearance of some dots from Figure 5 to Figure 6 is due to the lack of correlation values for the considered feature, the selected endpoint, and the two waves involved. Notably, Figure 6b displays a more scattered distribution compared to Figure 6a.



(**a**) Mobility features



(**b**) Oxford features

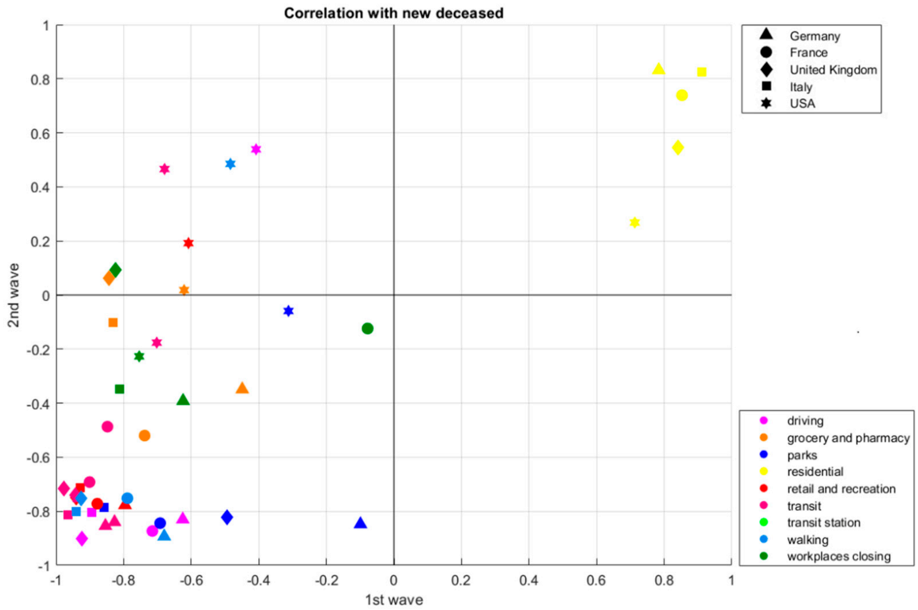
Figure 6. Correlation analysis—endpoint "new cases", 2nd wave vs. 3rd wave: (**a**) "mobility" features; (**b**) "Oxford" features. Matlab toolbox.

Whether a dot on the plot represents a specific combination of a feature and a country and is located near the bisector line, similar correlations occur when transitioning from the first to the second wave, as depicted in the plot. For instance, when considering the residential mobility feature (indicated by yellow dots in plots (a) of Figures 5 and 6), the five countries are clustered together, suggesting that they made similar decisions despite potential differences when transitioning from the second to the third periods, as evidenced by the comparison of Figures 5 and 6. Specifically, France, which exhibited a negative correlation in the third wave, transitioned from the first region (dot plot (a) in Figure 5) to the second region (dot plot (a) in Figure 6).

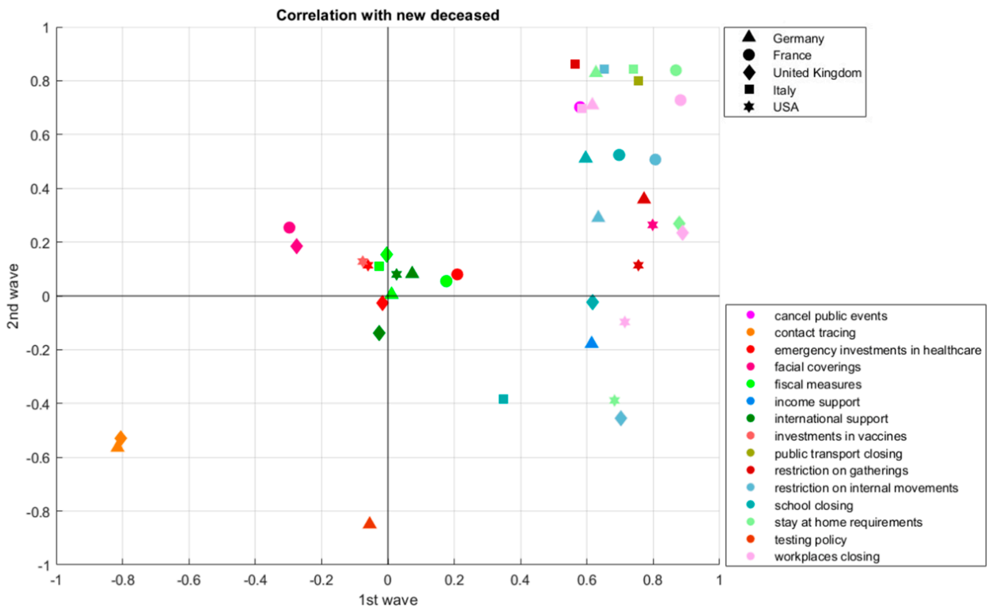
In Figure 5, dot plot (a) illustrates a region (the fourth) with positive correlation values in the first period and negative values in the second, but there are no dots. However, the same region in Figure 6a is full of dots. Several features significantly alter the level of correlation when transitioning from the first to the second wave period. For instance, the mobility features for Germany and France exhibit similar behaviors. Comparable patterns can also be observed for these countries when considering the Oxford Government responses/decisions and comparing the first and the third wave periods.

4.3. New Deaths—Comparative Analysis

Figures 7 and 8 present the correlation analysis for the new deaths endpoint and the previously selected and illustrated features, considering the period March 2020–April 2021, the selected countries, and the comparison between first and second waves and between second and third waves, respectively.

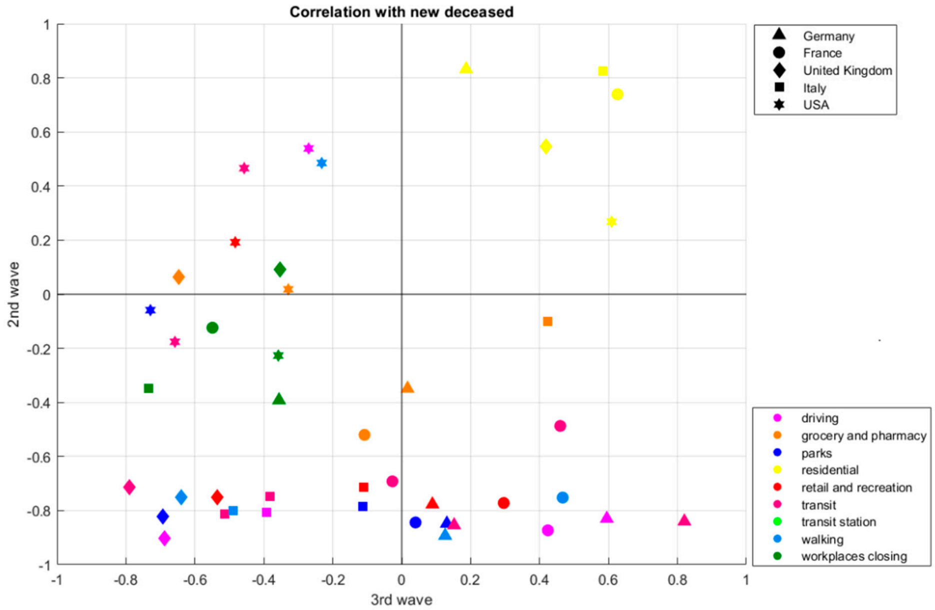


(**a**) Mobility features

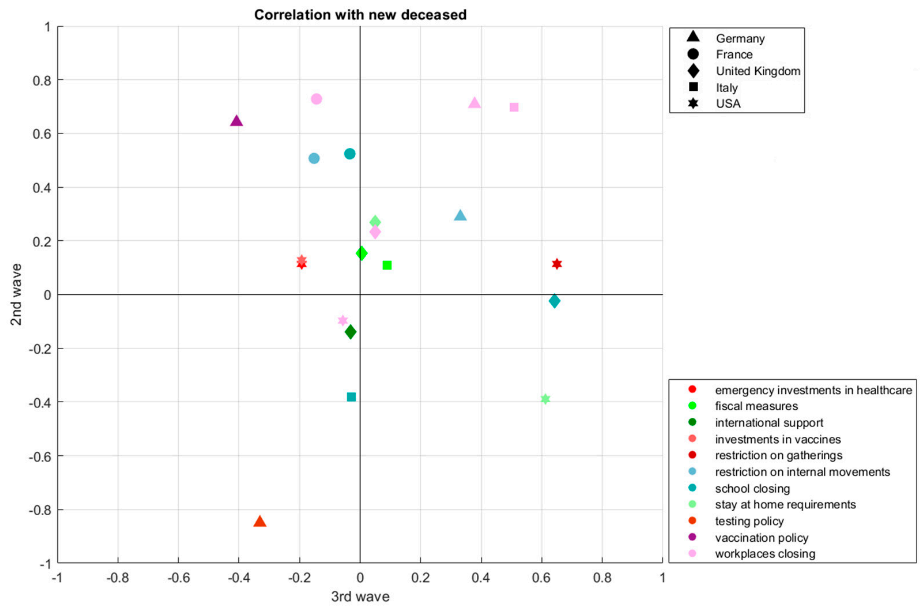


(**b**) Oxford features

Figure 7. Correlation analysis—endpoint "new deaths", 1st wave vs. 2nd wave: (**a**) "mobility" features; (**b**) "Oxford" features. Matlab toolbox.



(**a**) Mobility features



(**b**) Oxford features

Figure 8. Correlation analysis—endpoint "new deaths", 2nd wave vs. 3rd wave: (**a**) "mobility" features; (**b**) "Oxford" features. Matlab toolbox.

The absence of correlation values for this endpoint results in the non-existence of certain data points arising from the combination of features and countries. Notably, when considering France and Germany, mobility features exhibit significant changes between the first and third wave periods, as evidenced by their presence in all four regions of the dot plot in Figure 7a.

Upon comparing two dot plots—one representing new confirmed cases and the other new deaths—it becomes apparent that some dots share similar locations, indicating their presence in the same region and at similar levels. Conversely, there are also dots located in different regions. For instance, the residential mobility feature and France are depicted in different regions in the second and third plots.

5. Features Ranking Analysis

Relevant features are attributes that provide valuable information for determining the endpoint value. This section is dedicated to the feature selection process, which involves identifying relevant features and discarding irrelevant ones. The method used is a Relief-based algorithm as defined and classified by [19,20]. This analysis and ranking approach is conducted individually. It evaluates individual features by assigning them weights or scores based on their degree of relevance. The original Relief algorithm was formulated by [43], and one of its evolutions is RReliefF [44], which is an individual evaluation filter method implemented by the Orange toolbox.

The utilization of score-based analysis, underpinned by the relevant literature on data mining and machine learning techniques, serves to empower decision-makers in making well-informed choices by focusing on the most salient features. This is particularly crucial in the context of unforeseeable illnesses such as the COVID-19 pandemic. It is worth noting that the analyses conducted and presented in this study do not explicitly establish cause-and-effect relationships. However, they form the initial foundation for the identification and prediction of such relationships.

The ranked scores quantified for each feature by the RReliefF algorithm are presented in Tables 3 and 4. These scores are based on new confirmed cases and new deaths, respectively. The color scale in Table 3 is linked to the values, with low values shown in red and high values displayed in green. The ranking analyses are done for five selected countries ("FIVE COUNTRIES") and for each individual country (France, Germany, Italy, the UK, and the USA).

For each country, the ranked score is reported for the entire observation period ("ALL WAVES") and for each individual wave ("1st WAVE," "2nd WAVE," etc.). It is worth noting that the ranking order can vary significantly when considering the whole period compared to a single wave time window, indicating that the relevant features can differ between periods.

The sequence of features reported in the first column of Tables 3 and 4 aligns with the ranked values obtained from the FIVE COUNTRIES and ALL WAVES analysis. For example, workplace_closing is the first critical feature in Table 4 because in the FIVE COUNTRIES and ALL WAVES analysis, the RReliefF measure is 0.133.

When considering Italy and the endpoint of new confirmed cases, the most relevant features for the entire historical period are vaccination_policy followed by workplace_closing. However, different results are observed when analyzing individual waves. For the first wave, public_transport_closing followed by stay_at_home_requirements are most relevant, while for the second wave, vaccination_policy followed by retail_and_recreation are significant. In the third wave, workplace_closing followed by school_closing are the most relevant features. It is noteworthy that the relevance of features can vary between waves. For instance, school_closing is relevant for Italy in the whole period (rank = 3) but not in the second wave (rank = 11), and it is ranked 2 in the third wave. The most relevant feature in the second wave for Italy is vaccination_policy, which is consistent with the correlation measured for Italy and the endpoint of new confirmed cases. This confirms that different countries adopted different strategies and government responses to the pandemic.

Table 3. Ranking analysis for the new confirmed cases. Five-country analysis vs. single-country analyses. RReliefF by Orange toolbox.

	FR, DE, IT,UK, USA				FRANCE				GERMANY				ITALY				UK				USA			
	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd
vaccination_policy	0.102		0.111	0.105	0.067	0.197	0.130	0.131	0.058	0.171	0.050	0.126	0.188		0.148		0.029	0.024	0.058	0.096	0.021	0.064	0.064	0.048
restrictions_on_internal_movement	0.082	0.058	0.121	0.021	0.143	0.220	0.157	0.181	0.159	0.512	0.495	0.516	−0.009	0.056			0.065				0.084	−0.001	−0.001	−0.001
school_closing	0.078	0.020	0.047	0.186	0.111	0.122	0.184	0.070	0.053				0.104	0.024	0.065	0.250	0.123	0.049	0.126	0.179	0.212	0.208	0.097	0.083
workplace_closing	0.072	0.053	0.133	0.101	0.253	0.185	0.170	0.185	0.085	0.318	0.281	0.287	0.121	0.048	0.055	0.450	0.016	0.073	0.113	0.093	0.094	0.063	0.066	0.053
retail_and_recreation	0.068	0.090	0.099	0.057	0.089	0.068	0.062	0.084	0.074	0.195	0.195	0.207	0.092	0.132	0.147	0.169	0.078	0.129	0.115	0.122	0.065	0.063	0.064	0.082
workplaces	0.068	0.101	0.060	0.088	0.075	0.111	0.116	0.138	0.101	0.177	0.159	0.151	0.044	0.102	0.094	0.082	0.114	0.127	0.137	0.134	0.097	0.101	0.089	0.103
emergency investment_in_healthcare	0.062	0.002	0.020	0.061	0.003				0.001				0.035	0.009		0.008	−0.001				0.113	0.926	1.095	1.197
transit	0.061	0.088	0.074	0.063	0.082	0.149	0.152	0.133	0.058	0.210	0.213	0.224	0.055	0.094	0.081	0.240	0.067	0.094	0.120	0.139	0.055	0.139	0.132	0.145
stay_at_home_requirements	0.059	0.112	0.027	0.099	0.126				0.060				0.020	0.502			0.064	0.085	0.125	0.103	0.049	0.046	0.061	0.036
parks	0.058	0.046	0.061	0.080	0.063	0.173	0.193	0.192	0.075	0.256	0.241	0.234	0.045	0.060	0.060	0.202	0.086	0.098	0.100	0.099	0.104	0.155	0.174	0.176
walking	0.057	0.085	0.061	0.071	0.077	0.153	0.155	0.145	0.066	0.217	0.209	0.201	0.048	0.074	0.074	0.143	0.075	0.092	0.102	0.143	0.086	0.125	0.118	0.126
driving	0.055	0.084	0.065	0.074	0.068	0.149	0.160	0.145	0.058	0.185	0.179	0.199	0.041	0.071	0.074	0.161	0.089	0.112	0.122	0.150	0.084	0.133	0.132	0.142
residential	0.048	0.106	0.070	0.082	0.063	0.114	0.120	0.129	0.103	0.144	0.142	0.134	0.046	0.122	0.090	0.140	0.105	0.122	0.129	0.130	0.088	0.098	0.101	0.113
grocery_and_pharmacy	0.042	0.096	0.051	0.043	0.057	0.078	0.068	0.097	0.072	0.112	0.090	0.092	0.075	0.164	0.113	0.084	0.072	0.081	0.081	0.084	0.066	0.053	0.068	0.072
transit_stations	0.041	0.073	0.081	0.053	0.052	0.087	0.091	0.108	0.063	0.149	0.128	0.135	0.061	0.101	0.105	0.149	0.053	0.091	0.087	0.092	0.072	0.093	0.100	0.114
facial_coverings	0.038	0.297	0.045	0.024	0.089				0.069				0.013	0.482			0.009				0.212			
public_transport_closing	0.031	0.154	0.095	0.001	0.041				0.018				0.057	0.543	0.031		0.004				0.085			
cancel_public_events	0.030	0.001	0.031	0.001	0.088				0.010					0.024			0.008				0.029	0.006	0.002	0.001
testing_policy	0.025	0.028	0.075	0.025	0.086				0.093	0.512	0.495	0.516		0.051			0.004				0.032			
debt_relief	0.017	0.126	0.051	0.015	0.050				0.018				0.010	0.084			0.004				0.101			
restrictions_on_gatherings	0.012	0.147	0.038	0.033	0.007				0.044				−0.001	0.048	0.086		0.008		0.001	0.023	0.088	0.018	0.040	0.023
income_support	0.006	0.143	0.082	0.002	0.023				0.048				0.001	0.132			0.004				0.101			
contact_tracing	0.004	0.012	0.040	0.011	0.055	0.100	0.069	0.067	0.023								0.027				0.013			
international_support	0.001	0.001	0.001	0.065	−0.001				0.001								0.006	0.001	0.010	0.011	0.090			
fiscal_measures	0.001	0.002	0.001	0.055	−0.001				0.001				0.003	0.009	0.008	0.008	0.006	0.067	0.023	0.009	0.063	0.835	0.969	1.082
investment_in_vaccines	0.001	0.001	0.001	0.043	−0.001				0.001								0.001	0.122	0.022	0.025	0.090	0.926	1.095	1.197
public information_campaigns	−0.002	−0.005			0.007				0.000												0.037			
international_travel_controls	−0.009	0.041	0.001	0.037	0.023				0.047				0.001	0.031			0.082	0.155	0.120	0.126	0.034			

Table 4. Ranking analysis for the new deaths. Five-country analysis vs. single-country analyses. RReliefF by Orange toolbox.

	FR, DE, IT,UK, USA				FRANCE				GERMANY				ITALY				UK				USA			
	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd	All Waves	1st	2nd	3rd
vaccination_policy	0.101		0.162	0.258	0.068			0.241	0.141	0	0.06	0.132	0.057		0.27		0.07			0.087	0.071			0.2
restrictions_on_internal_movement	0.096	0.005	0.116	0.044	0.083	0.015	0.173	0.182	0.283	0.04	0.303	0.45	0.098	0.073			0.067	0.046	0.266		0.041	0.035		0.204
school_closing	0.066	−0.007	0.023	0.126	0.106	0.019	0.156	0.17	−0.006	0.137	−0.016		0.077	0.003	−0.001	0.193	0.039	0.061	0.256	0.165	0.08	0.011		0.179
workplace_closing	0.133	0.022	0.127	0.154	0.175	0.025	0.358	0.103	0.066	0.271	0.001	0.278	0.16	0.054	0.169	0.431	0.024	0.095	0.061	0.093	0.094	0.038	0.023	0.193
retail_and_recreation	0.065	0.078	0.108	0.066	0.081	0.071	0.163	0.072	0.104	0.0122	0.075	0.181	0.098	0.167	0.117	0.182	0.1	0.103	0.243	0.091	0.057	0.092	0.065	0.074
workplaces	0.073	0.093	0.11	0.094	0.088	0.106	0.066	0.098	0.096	0.109	0.074	0.157	0.057	0.132	0.072	0.093	0.118	0.131	0.133	0.108	0.09	0.127	0.133	0.103
emergency investment_in_healthcare	0.001	0.404	0.066	0.001	0.001	0.032	0.015		0.001	0.086			0.005	0.047		0.014	0.063	−0.001	0.075		0.167	0.003	0.258	1.204
transit	0.043	0.038	0.083	0.069	0.136	−0.075	0.145	0.097	0.123	0.16	0.06	0.285	0.051	0.088	0.063	0.259	0.081	0.065	0.39	0.104	0.061	0.084	0.145	0.125
stay_at_home_requirements	0.02	0.175	0.041	0.057	0.092	0.029	0.046		0.011	0.196	0.013		0.179	0.394			0.125	0.285	0.204	0.092	0.076	0.036	0.221	0.193
parks	0.051	0.047	0.047	0.088	0.045	0.036	0.057	0.164	0.057	0.12	0.06	0.285	0.051	0.088	0.063	0.259	0.081	0.065	0.39	0.104	0.061	0.084	0.145	0.125
walking	0.056	0.04	0.088	0.066	0.137	0.068	0.105	0.111	0.117	0.213	0.043	0.269	0.042	0.064	0.056	0.167	0.078	0.06	0.231	0.084	0.094	0.136	0.157	0.116
driving	0.054	0.05	0.074	0.064	0.135	0.08	0.1	0.084	0.074	0.096	0.043	0.135	0.058	0.12	0.086	0.162	0.068	0.099	0.231	0.081	0.068	0.096	0.145	0.104
residential	0.068	0.106	0.095	0.087	0.071	0.131	0.088	0.121	0.098	0.119	0.073	0.141	0.071	0.142	0.066	0.138	0.119	0.152	0.222	0.108	0.099	0.165	0.185	0.11
grocery_and_pharmacy	0.069	0.098	0.082	0.057	0.062	0.088	0.106	0.065	0.1	0.098	0.04	0.104	0.081	0.148	0.082	0.107	0.086	0.105	0.16	0.069	0.054	0.078	0.103	0.071
transit_stations	0.053	0.064	0.096	0.064	0.058	0.056	0.1	0.084	0.074	0.096	0.043	0.135	0.058	0.12	0.086	0.162	0.068	0.099	0.231	0.081	0.068	0.096	0.145	0.104
facial_coverings	0.058	0.267	0.063	0.024	0.072	0.004	−0.001		0.018	0.434	0	0	0.117	0.39			0.1	0.404	−0.001		0.19	0.246	0.2	0.187
public_transport_closing	0.07	0.137	0.031	0.003	0.067	0.018			0.188	0	0.212		0.148	0.475	0.001		0.014	0.058	0.16	0.069	0.054	0.078	0.103	0.071
cancel_public_events	−0.004	−0.009	0.008	0.013	0.061	−0.01	0.161		−0.002	−0.002			−0.001	0.003			0.016	0.066			0.04	0.022		0.197
testing_policy	0.032	0.049	0.038	0.037	0.076	0.008			0.158	0.146	0.172	0.45	0.001	0.009			0.018	0.024		0.089	0.011	0.006		0.196
debt_relief	0.015	0.082	0.034	0.011	0.071	0.071	0.034		0.012	0.44			0.031	0.156			0.004	0.047			0.143	0.118		
restrictions_on_gatherings	0.018	0.063	0.017	0.021	0.001	−0.009			−0.007	0.109	−0.015		0.08	0.079	0.14		0.062	0.058			0.075	0.056	0.15	0.134
income_support	0.02	0.084	0.022		0.003	−0.003			0.053	0.001	0.163		0.017	0.274			0.014	0.058			0.143	0.118		
contact_tracing	0.022	0.022	0.111	0.018	0.057	0.006		0.14	0.142	0.084	0.142						0.011	0.062	0.016		0.014			0.217
international_support	0.001	0.01	0.002			0.003			0	0.003	0.002						0.001	−0.001	−0.001	0.008	0.102	0.003	0.258	1.204
fiscal_measures	0.001	0.012	0.003	0.001	0.001	0.022	0.006		0.001	0.083	0.019		0.003	0.007	0.003	0.014	0.002	0.004	0.014	0.028	0.07	0.001		1.088
investment_in_vaccines	0.001	0.004	0.054	0.001	0.001	0.002			0.001	0.105			−0.002		−0.001		−0.001	0.013		−0.001	0.1	0.033	0.046	1.204
public information_campaigns		−0.009			0.001	−0.008															0.017	0.037		0.197
international_travel_controls	0.024	0.017	0.015		0.003	−0.03			0.004	0.077			0.074	0.054			0.018	0.024		0.089	0.011	0.006		0.196

6. Discussion and Concluding Remarks

The four-step-based correlation and feature selection analysis conducted in this study differs from the existing literature contributions for the following main issues simultaneously supported by a quantitative approach:

- Dynamic database collecting categorical and continuous attributes data from multiple sources of different typologies (population demographics, geography, health, government, community mobility, traffic, patients on hospitals, COVID infections);
- Time-based database that supports comparative analyses on different periods and waves of the COVID-19 pandemic;
- Focus on a selection of homogeneous and comparable countries in order to support comparative analyses;
- Correlation-based analysis and feature ranking analyses;
- Database availability for further research. This repository could also host new attributes coming from other additional sources, e.g., related to climate indicators or vaccines distributions;
- Adoption of an open-source data mining and machine learning toolbox;
- The result of the analysis confirms an essential role of the travel restriction and social distancing among the most adopted measures of governments to mitigate the effects of the pandemic;
- Findings in this study could assist the governmental policymaking in the near future thanks to a comparative approach that involves a wide period of observation and multiple homogeneous countries;
- The focus on non-pharmaceutical measures during periods in absence of a mass spread of vaccines makes these analyses useful to support the decision-making process in future pandemics when vaccines are still not available.

The sum of the ranking positions for each feature and each country given the ranking analyses illustrated in Tables 3 and 4 on the whole set of data (see the so called "ALL" type analysis) are reported in Appendix D. For example, given the school closing feature, the global score (see the "global ranking score" in Appendix D) is 25, which is the sum of rank 3 for Italy, rank 4 for France, rank 16 for Germany, and rank 1 for the UK and USA. This is an additional list of summary results coming from the feature ranking analysis:

- When the target endpoint is the new confirmed cases, school closing (1), workplaces closing (2), workplaces (3), parks (4), and residential (5) are the most significant attributes for the selected response. This group of features changes passing to the new deaths endpoint: facial coverings (1), driving (2), stay at home requirements (3), residential (4), and workplaces closing (5). Residential and workplaces closing are two most significant attributes for both endpoints.
- School closing is part of the selection of most five significant attributes in three of the five countries for the new confirmed endpoint.
- Facial coverings is part of the selection of most five significant attributes in four of the five countries for the new confirmed endpoint.
- Given the target new confirmed cases and the set of five most significant attributes, two are Oxford government responses (school closing and workplaces closing) and three are google mobility features (workplaces, parks, and residential).
- Given the target new deaths and the set of five most significant attributes, two are Oxford government responses (facial coverings and stay at home requirements), one is an Apple mobility feature (driving) and two are Google mobility features (residential and workplaces closing).

This study's time-based approach can facilitate new quantitative analyses of available and historical datasets capturing daily new records. It is imperative to conduct criticality analyses and select relevant features that consider the combined effects of various decisions, such as different government strategies, on specific endpoints.

Future research should aim to explore the effectiveness of prediction models for forecasting, operating on the extensive set of categorical and continuous attributes, features, and endpoints. Consequently, this study provides readers, planners, and policymakers, specializing in various research fields, with the opportunity to work with an integrated database, which is an additional research deliverable.

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Appendix A. Feature Descriptions and Classification

Data Source Typology	Feature/Attribute	Type of Attribute	Description
Auxiliary attributes	Key	C	Unique string identifying the region, e.g., US_CA
	Date	T	Date [aaaa-mm-gg]
	Time index	N	Progressive index of time
	ONDATA	C	Wave number (1st–2nd–3rd wave period) for the single country
	State	C	Region name
Population demographics	Population	N	Total counts of humans
	Population_male	N	Total count of males
	Population_female	N	Total count of females
	Rural_population	N	Population in a rural area
	Urban_population	N	Population in an urban area
	Population_density	N	Population per squared kilometer of a land area
	HDI	N	Composite index of life expectancy, education and per capita income indicators
	Pop_age_00_09	N	Estimated population between the ages of {lower} and {upper}, both inclusive
	Pop_age_10_19	N	
	Pop_age_20_29	N	
	Pop_age_30_39	N	
	Pop_age_40_49	N	
	Pop_age_50_59	N	
	Pop_age_60_69	N	
	Pop_age_70_79	N	
	Pop_age_80_89	N	
	Pop_age_90_99	N	
	Pop_age_80_and_older	N	

Data Source Typology	Feature/Attribute	Type of Attribute	Description
Geography	Latitude	N	Floating point representing the geographic coordinate
	Longitude	N	Floating point representing the geographic coordinate
	Area	N	Area encompassing this region
	Rural_area	N	Area encompassing rural land in this region
	Urban_area	N	Area encompassing urban land in this region
Health related indicators	Life_expectancy	N	Average years that an individual is expected to live
	Smoking_prevalence	N	Percentage of smokers in population
	Diabetes_prevalence	N	Percentage of persons with diabetes in population
	Infant_mortality_rate	N	Infant mortality rate (per 1.000 live births)
	Male_mortality_rate	N	Mortality rate, adult, male (per 1.000 male adult)
	Female_mortality_rate	N	Mortality rate, adult, female (per 1.000 female adult)
	Pollution_mortality_rate	N	Mortality rate attributed to household and ambient air pollution, age-standardized (per 100.000 population)
	Comorbidity_mortality_rate	N	Mortality from cardiovascular disease, cancer, diabetes or cardiorespiratory disease between exact ages 30 and 70
	Hospital_beds	N	Hospital beds (per 1.000 people)
	Nurses	N	Nurses and midwives (per 1.000 people)
	Physicians	N	Physicians (per 1.000 people)
	Health_expenditure	N	Health expenditure per capita
	Out_of_pocket_health_expenditure	N	Out of pocket expenditure per capita
Oxford COVID-19 government response	School_closing	C	School closures: 0—no measures; 1—recommend closing; 2—require closing (only some levels or categories, e.g., just high school, or just public school); 3—require closing all levels
	Workplaces_closing	C	Workplace closures: 0—no measures; 1—recommend closing (or work from home); 2—require closing (or work from home) for some sectors or categories of workers; 3—require closing (or work from home) all but essential workplaces (e.g., grocery stores, doctors)
	Cancel_public_events	C	Cancel public events: 0—no measures; 1—recommend cancelling; 2—require cancelling
	Restrictions_on_gatherings	C	Restrictions on gatherings: 0—no restrictions; 1—restrictions on very large gatherings (the limit is above 1.000 people); 2—restrictions on gatherings between 100–1000 people; 3—restrictions on gatherings between 10–100 people; 4—restrictions on gatherings of less then 10 people
	Public_transport_closing	C	Close public transport: 0—no measures; 1—recommend closing (or significantly reduce volume/route/means of transport available); 2—require closing (or prohibit most citizens from using it)
	Stay_at_home_requirements	C	Stay at home: 0—no measures; 1—recommend not leaving house; 2—require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips; 3—require not leaving house with minimal exceptions (e.g., allowed to leave only once every few days, or only one person can leave at a time, etc.)
	Restrictions_on_internal_movement	C	Restrictions on internal movement: 0—no measures; 1—recommend movement restrictions; 2—restrict movement
	International_travel_controls	C	International travel controls: 0—no measures; 1—screening; 2—quarantine arrivals from high-risk regions; 3—ban on high-risk regions; 4—total border closure
	Public_information_campaigns	C	Public information campaigns: 0—no COVID-19 public information campaigns; 1—public officials urging caution about COVID-19; 2—coordinated public information campaign (e.g., across traditional and social media)
	Testing_policy	C	Testing policy: 0—no testing policy; 1—only those who both (a) have symptoms and (b) meet specific criteria (e.g., key workers, admitted to hospital, came into contact with a known case, returned from overseas); 2—testing on anyone showing COVID-19 symptoms; 3—open public testing (e.g., "drive through" testing available to asymptomatic people)

Data Source Typology	Feature/Attribute	Type of Attribute	Description
Oxford COVID-19 government response	Contact_tracing	C	Contact tracing: 0—no contact tracing; 1—limited contact tracing—not done for all cases; 2—comprehensive contact tracing—done for all cases
	Facial_coverings	C	Face coverings: 0—no policy; 1—recommended; 2—required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible; 3—required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible; 4—required outside the home at all time regardless of location or presence of other people
	Vaccination_policy	C	Vaccination policy: 0—no availability; 1—availability for ONE of following: key workers/clinically vulnerable groups/elderly groups; 2—availability for TWO of following: key workers/clinically vulnerable groups/elderly groups; 3—availability for ALL of following: key workers/clinically vulnerable groups/elderly groups; 4—availability for all three plus partial additional availability (select broad groups/ages)
	Income_support	N	Value of fiscal stimuli, including spending or tax cuts
	Debt_relief	N	Debt/contract relief for households
	Fiscal_measures	N	Value of fiscal stimuli, including spending or tax cuts
	International_support	N	Giving international support to other countries
	Emergency_investments_in_healthcare	N	Emergency funding allocated to healthcare
	Investments_in_vaccines	N	Emergency funding allocated to vaccine research
	Stringency_index	N	Overall stringency index equal to the sum of categorial features' values of government restrictions normalized to 100
Google COVID-19 community mobility	Retail_and_recreation	N	Percentage change in visits to restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters compared to baseline
	Grocery_and_pharmacy	N	Percentage change in visits to place like grocery markets, food warehouses, farmer markets, specialty food shops, drug stores, and pharmacies compared to baseline
	Parks	N	Percentage change in visits to places like local parks, public beaches, marinas, dog parks, plazas, and public gardens compared to baseline
	Transit_stations	N	Percentage change in visits to places like public transport hubs such as subway, bus and train stations compared to baseline
	Workplaces	N	Percentage change in visits to places of work compared to baseline
	Residential	N	Percentage change in visits to places of residence compared to baseline
Apple COVID-19 community mobility	Walking	N	Percentage change in walking mobility
	Driving	N	Percentage change in mobility by car
	Transit	N	Percentage change in mobility with public transport
Air traffic data	Departure_flight	N	Number of IFR departures
	Arrival_flight	N	Number of IFR arrivals
	Total_flight	N	Number of total IFR movements
Patients of COVID-19 and hospitals	Current_intensive_care	N	Count of current (active) cases admitted into ICU after a positive COVID-19 test to date
COVID-19 infections	New_confirmed	N	Count of new confirmed after positive test on this date
	New_recovered	N	Count of new recoveries from a positive COVID-19 case on this date
	New_tested	N	Count of new COVID-19 tests performed on this date
	New_deceased	N	Count of new deaths from a positive COVID-19 case on this date

Appendix B. Spearman Correlation Values, Oxford Government Responses

(a) New Cases Endpoint.

Oxford Government Response	Correlations with New Cases		
	First Wave	**Second Wave**	**Third Wave**
School closing	2.717	0.152	1.020
France	0.564	0.307	−0.447
Germany	0.637	0.130	
Italy	0.355	−0.413	0.462
United Kingdom	0.628	0.128	0.495
USA	0.533		0.510
Workplaces closing	3.251	1.509	0.462
France	0.658	0.664	0.381
Germany	0.382	0.343	−0.393
Italy	0.580	0.624	0.507
United Kingdom	0.903	0.228	−0.175
USA	0.728	−0.350	0.142
Cancel public events	2.556	0.436	0.234
France	0.323	0.436	
Germany	0.601		
Italy	0.355		
United Kingdom	0.629		
USA	0.648		0.234
Restrictions on gatherings	2.995	1.408	0.432
France	0.461		
Germany	0.486	0.381	
Italy	0.678	0.843	
United Kingdom	0.596		0.006
USA	0.774		0.426
Public transport closing	2.538	1.286	
France	0.437		
Germany		0.511	
Italy	0.758	0.775	
United Kingdom	0.629		
USA	0.714		
Stay at home requirements			
France	3.658	2.462	0.398
Germany	0.604	0.646	
Italy	0.769	0.678	
United Kingdom	0.711	0.815	
USA	0.878	0.402	−0.168
	0.696	−0.079	0.566
Restriction on internal movement			
France	3.125	0.445	−0.049
Germany	0.506	0.132	0.187
Italy	0.461	0.068	−0.407
United Kingdom	0.702	0.815	
USA	0.725	−0.057	
	0.731		0.171
International travel control	1.295		−0.268
France	0.490		
Germany	0.823		
Italy	−0.146		
United Kingdom	−0.352		−0.268
USA	0.480		

(a) New Cases Endpoint.			
Oxford Government Response	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Public information campaigns			
France	1.102		
USA	0.398		
	0.704		
Testing policy	−0.078	−0.665	0.407
France	−0.631		
Germany	−0.268	−0.665	0.407
Italy	0.399		
United Kingdom	−0.251		
USA	0.673		
Contact tracing	−1.570	−0.749	−0.444
France	−0.252		−0.444
Germany	−0.553	−0.160	
United Kingdom	−0.765	−0.589	
Facial coverings	0.207	1.081	
France	−0.219	0.305	
Germany	0.079		
Italy	−0.199		
United Kingdom	−0.195	0.234	
USA	0.741	0.542	
Vaccination policy		0.303	0.065
France			0.459
Germany		0.223	0.216
Italy		0.080	
United Kingdom			−0.523
USA			−0.087
Income support	2.635	−0.263	
France	0.509		
Germany	0.520	−0.263	
Italy	0.168		
United Kingdom	0.629		
USA	0.809		
Debt relief	1.954	−0.704	
France	0.630	−0.704	
Germany	0.274		
Italy	−0.400		
United Kingdom	0.641		
USA	0.809		
Fiscal measures	0.225	0.382	0.090
France	0.106	0.057	
Germany	0.083	0.061	
Italy	0.043	0.116	0.208
United Kingdom	0.029	0.148	0.039
USA	−0.036		−0.157
International support	0.178	0.196	0.011
France	0.123		
Germany	0.059	0.116	
United Kingdom	−0.021	−0.072	0.011
USA	0.017	0.152	

(a) New Cases Endpoint.

Oxford Government Response	Correlations with New Cases		
	First Wave	Second Wave	Third Wave
Emergency investments in healthcare			
France	0.407	−0.108	0.042
Germany	0.213	0.108	
Italy	0.153		
United Kingdom	0.105		0.208
USA	−0.028	0.069	
	−0.036	−0.285	−0.166
Investments in vaccines	0.065	0.081	−0.023
France	0.048		
Germany	0.115		
Italy		−0.127	
United Kingdom	0.010		0.143
USA	−0.108	0.208	−0.166
Stringency index	2.524	1.613	1.670
France	0.507	0.629	0.323
Germany	0.503	0.293	0.210
Italy	0.769	0.537	0.612
United Kingdom	−0.014	−0.126	−0.093
USA	0.759	0.280	0.618

(b) New Deaths.

Oxford Government Response	Correlations with New Cases		
	First Wave	Second Wave	Third Wave
School closing	2.787	0.629	0.602
France	0.697	0.524	−0.034
Germany	0.596	0.511	
Italy	0.348	−0.382	−0.028
United Kingdom	0.617	−0.024	0.641
USA	0.529		0.023
Workplaces closing	3.684	2.272	0.735
France	0.882	0.728	−0.144
Germany	0.616	0.709	0.378
Italy	0.585	0.698	0.508
United Kingdom	0.887	0.234	0.050
USA	0.714	−0.097	−0.057
Cancel public events	2.715	0.702	0.261
France	0.579	0.702	
Germany	0.569		
Italy	0.348		
United Kingdom	0.586		
USA	0.633		0.261
Restrictions on gatherings	3.105	1.334	0.606
France	0.462		
Germany	0.772	0.359	
Italy	0.563	0.861	
United Kingdom	0.553		−0.044
USA	0.755	0.114	0.650
Public transport closing	2.818	1.606	
France	0.778		
Germany		0.805	
Italy	0.756	0.801	
United Kingdom	0.584		
USA	0.700		

(b) New Deaths.			
Oxford Government Response	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Stay at home requirements			
France	3.795	2.392	0.663
Germany	0.868	0.839	
Italy	0.627	0.829	
United Kingdom	0.739	0.843	
USA	0.878	0.270	0.051
	0.683	−0.389	0.612
Restriction on internal movement			
France	3.513	1.184	0.403
Germany	0.806	0.507	−0.152
Italy	0.634	0.290	0.331
United Kingdom	0.653	0.843	
USA	0.703	−0.456	
	0.717		0.224
International travel control			0.018
France	1.339		
Germany	0.585		
Italy	0.857		
United Kingdom	−0.181		0.018
USA	−0.412		
	0.490		
Public information campaigns			
France	1.080		
USA	0.389		
	0.691		
Testing policy	−0.042	−0.849	−0.331
France	−0.764		
Germany	−0.055	−0.849	−0.331
Italy	0.403		
United Kingdom	−0.290		
USA	0.664		
Contact tracing	−1.887	−1.095	−0.065
France	−0.267		−0.065
Germany	−0.815	−0.564	
United Kingdom	−0.805	−0.531	
Facial coverings	0.551	0.703	
France	−0.297	0.254	
Germany	0.401		
Italy	−0.075		
United Kingdom	−0.276	0.185	
USA	0.798	0.264	
Vaccination policy		0.917	−0.605
Germany		0.642	−0.408
Italy		0.275	
United Kingdom			−0.528
USA			0.331
Income support	2.879	−0.178	
France	0.587		
Germany	0.614	−0.178	
Italy	0.302		
United Kingdom	0.584		
USA	0.792		

(b) New Deaths.			
Oxford Government Response	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Fiscal measures	0.098	0.324	−0.090
France	0.176	0.055	
Germany	0.011	0.005	
Italy	−0.026	0.109	0.089
United Kingdom	−0.003	0.155	0.004
USA	−0.060		−0.183
International support	0.204	0.024	−0.032
France	0.131		
Germany	0.073	0.082	
United Kingdom	−0.026	−0.138	−0.032
USA	0.026	0.080	
Emergency investments in healthcare			
France	0.354	0.167	−0.104
Germany	0.209	0.080	
Italy	0.109		
United Kingdom	0.113		0.089
USA	−0.017	−0.027	
	−.060	0.114	−0.193
Investments in vaccines	0.083	0.004	−0.114
France	0.071		
Germany	0.124		
Italy		−0.124	
United Kingdom	−0.036		0.079
USA	−0.076	0.128	−0.193
Stringency index	3.037	1.777	0.847
France	0.802	0.801	−0.112
Germany	0.735	0.595	−0.241
Italy	0.767	0.702	0.384
United Kingdom	−0.080	−0.205	0.156
USA	0.813	−0.116	0.660

Appendix C. Spearman Correlation Values, Oxford Government Responses

(a) Mobility Features. New Cases Endpoint.			
Mobility	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Retail and recreation	−3.82	−2.416	−0.560
France	−0.675	−0.685	−0.200
Germany	−0.722	−0.569	0.722
Italy	−0.850	−0.716	−0.413
United Kingdom	−0.852	−0.513	−0.178
USA	−0.721	−0.067	−0.491
Grocery and pharmacy	−3.180	−0.306	0.193
France	−0.532	−0.542	0.142
Germany	−0.419	−0.036	0.300
Italy	−0.755	−0.148	0.408
United Kingdom	−0.803	0.270	−0.378
USA	−0.671	0.150	−0.279

(a) Mobility Features. New Cases Endpoint.			
Mobility	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Parks	−2.135	−2.590	−0.400
France	−0.474	−0.741	0.246
Germany	−0.153	−0.756	0.590
Italy	−0.798	−0.682	−0.057
United Kingdom	−0.375	−0.701	−0.584
USA	−0.335	0.290	−0.595
Transit stations	−3.997	−2.149	−0.544
France	−0.666	−0.387	0.256
Germany	−0.818	−0.659	0.411
Italy	−0.842	−0.676	−0.289
United Kingdom	−0.917	−0.586	−0.384
USA	−0.734	0.159	−0.538
Workplaces	−3.664	−0.579	−1.081
France	−0.627	0.116	0.249
Germany	−0.675	−0.176	−0.496
Italy	−0.789	−0.224	−0.217
United Kingdom	−0.886	−0.025	−0.332
USA	−0.687	−0.270	−0.285
Residential	3.786	2.595	1.610
France	0.644	0.389	−0.136
Germany	0.766	0.733	0.421
Italy	0.847	0.770	0.476
United Kingdom	0.867	0.565	0.359
USA	0.662	0.138	0.490
Walking	−3.479	−2.343	−0.447
France	−0.542	−0.586	0.467
Germany	−0.713	−0.732	0.126
Italy	−0.836	−0.727	−0.222
United Kingdom	−0.836	−0.615	−0.505
USA	−0.552	0.317	−0.313
Driving	−3.253	−2.527	−0.286
France	−0.486	−0.754	0.424
Germany	−0.667	−0.706	0.595
Italy	−0.817	−0.768	−0.393
United Kingdom	−0.785	−0.758	−0.522
USA	−0.498	0.459	−0.390
Transit	−3.974	−2.098	−0.436
France	−0.632	−0.236	0.460
Germany	−0.818	−0.702	0.820
Italy	−0.858	−0.811	−0.469
United Kingdom	−0.893	−0.529	−0.596
USA	−0.773	0.180	−0.651
(b) Mobility Features. New Deaths Endpoint.			
Mobility	**Correlations with New Deaths**		
	First Wave	**Second Wave**	**Third Wave**
Retail and recreation	−4.152	−2.820	−0.742
France	−0.878	−0.772	0.296
Germany	−0.796	−0.777	0.089
Italy	−0.929	−0.713	−0.110
United Kingdom	−0.941	−0.750	−0.534
USA	−0.608	0.192	−0.483

(b) Mobility Features. New Deaths Endpoint.			
Mobility	**Correlations with New Deaths**		
	First Wave	**Second Wave**	**Third Wave**
Grocery and pharmacy			
France	−3.482	−0.890	−0.644
Germany	−0.738	−0.520	−0.108
Italy	−0.449	−0.349	0.017
United Kingdom	−0.831	−0.101	0.424
USA	−0.843	0.062	−0.648
	−0.621	0.018	−0.329
Parks	−2.454	−3.360	−1.363
France	−0.692	−0.844	0.040
Germany	−0.099	−0.848	0.131
Italy	−0.857	−0.786	−0.113
United Kingdom	−0.494	−0.823	−0.692
USA	−0.312	−0.059	−0.729
Transit stations	−4.338	−3.212	−0.916
France	−0.901	−0.692	−0.027
Germany	−0.854	−0.854	0.152
Italy	−0.937	−0.749	−0.383
United Kingdom	−0.944	−0.741	
USA	−0.702	−0.176	−0.658
Workplaces	−3.091	−1.000	−2.350
France	−0.077	−0.124	−0.549
Germany	−0.624	−0.392	−0.356
Italy	−0.812	−0.349	−0.735
United Kingdom	−0.824	0.092	−0.352
USA	−0.754	−0.227	−0.358
Residential	4.103	3.210	2.424
France	0.853	0.739	0.626
Germany	0.784	0.832	0.187
Italy	0.912	0.824	0.583
United Kingdom	0.841	0.547	0.419
USA	0.713	0.268	0.609
Walking	−3.821	−2.712	−0.769
France	−0.789	−0.752	0.467
Germany	−0.680	−0.893	0.126
Italy	−0.941	−0.801	−0.490
United Kingdom	−0.927	−0.751	−0.640
USA	−0.484	0.485	−0.232
Driving	−2.870	−2.870	−0.329
France	−0.873	−0.873	0.424
Germany	−0.830	−0.830	0.595
Italy	−0.805	−0.805	−0.391
United Kingdom	−0.901	−0.901	−0.687
USA	0.539	0.539	−0.270
Transit	−2.338	−2.388	−0.481
France	−0.487	−0.487	0.460
Germany	−0.840	−0.840	0.820
Italy	−0.812	−0.812	−0.514
United Kingdom	−0.715	−0.715	−0.790
USA	0.466	0.466	−0.457

(c) Air Traffic Data. New Cases Endpoint.			
Air Traffic Data	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Departure flight	−2.557	−2.537	0.287
France	−0.509	−0.589	−0.150
Germany	−0.556	−0.588	0.233
Italy	−0.681	−0.642	0.006
United Kingdom	−0.881	−0.718	0.198
Arrival flight	−2.564	−2.528	0.102
France	−0.516	−0.603	−0.171
Germany	−0.555	−0.584	0.135
Italy	−0.677	−0.636	−0.052
United Kingdom	−0.816	−0.705	0.190
Total flight	−2.564	−2.534	0.109
France	−0.514	−0.596	−0.160
Germany	−0.556	−0.585	0.135
Italy	−0.679	−0.640	−0.061
United Kingdom	−0.815	−0.713	0.195
(d) Air Traffic Data. Deaths Endpoint.			
Air Traffic Data	**Correlations with New Deaths**		
	First Wave	**Second Wave**	**Third Wave**
Departure flight	−3.459	−3.270	−0.281
France	−0.851	−0.781	0.302
Germany	−0.859	−0.797	−0.122
Italy	−0.848	−0.820	−0.239
United Kingdom	−0.901	−0.872	−0.222
Arrival flight	−3.459	−3.255	−0.111
France	−0.855	−0.783	0.305
Germany	−0.854	−0.792	0.054
Italy	−0.847	−0.819	−0.242
United Kingdom	−0.903	−0.861	−0.228
Total flight	−3.462	−3.264	−0.116
France	−0.854	−0.782	0.306
Germany	−0.857	−0.794	0.054
Italy	−0.848	−0.820	−0.253
United Kingdom	−0.903	−0.868	−0.223
(e) Hospital and Infections. New Cases Endpoint.			
Hospital and Infections	**Correlations with New Cases**		
	First Wave	**Second Wave**	**Third Wave**
Current intensive care	1.134	1.617	0.852
France	0.376	0.779	0.438
Italy	0.758	0.838	0.414
New deceased	4.015	3.579	1.688
France	0.664	0.721	−0.136
Germany	0.754	0.808	0.004
Italy	0.870	0.804	0.281
United Kingdom	0.914	0.826	0.855
USA	0.813	0.420	0.684
New recovered	−0.037	1.436	0.675
France	0.390	0.713	0.499
Italy	0.353	0.723	0.176
New tested	−0.655	2.203	0.935
France	−0.344	0.396	0.029
Italy	−0.037	0.758	0.814
United Kingdom	−0.575	0.718	−0.485
USA	0.301	0.331	0.577

(f) Hospital and Infections. New Cases Endpoint.			
Hospital and Infections	**Correlations with New Deaths**		
	First Wave	**Second Wave**	**Third Wave**
Current intensive care	1.525	1.868	0.564
France	0.680	0.928	0.020
Italy	0.845	0.940	0.544
New deceased	4.015	3.579	1.688
France	0.664	0.721	−0.136
Germany	0.754	0.808	0.004
Italy	0.870	0.804	0.281
United Kingdom	0.914	0.826	0.855
USA	0.813	0.420	0.684
New recovered	0.001	1.847	0.750
France	−0.532	0.912	−0.045
Italy	0.536	0.935	0.795
New tested	−0.664	2.444	1.200
France	−0.423	0.574	0.646
Italy	0.035	0.697	0.418
United Kingdom	−0.675	0.763	−0.334
USA	0.399	0.410	0.470

Appendix D. Summary Results on Feature Ranking Analysis: (a) the New Confirmed Cases vs. (b) the New Deaths

(a) New Confirmed Cases.		
Target: New Confirmed per 100.000		
Feature	**Global Ranking Score**	**Times in First 5 Positions**
School closing	25	4
Workplaces closing	32	3
Workplaces	35	2
Parks	40	2
Residential	42	2
Retail and recreation	42	2
Debt relief	45	0
Walking	50	0
Contact tracing	53	0
Grocery and pharmacy	56	1
Restriction on internal movement	58	2
Facial coverings	59	1
Transit	61	0
Emergency investments in healthcare	62	1
Stay at home requirements	64	1
Transit station	65	0
Driving	84	1
Income support	85	1
Public transport closing	85	0
Testing policy	85	1
Fiscal measures	87	0
International travel control	89	0
Cancel public events	96	0
Restriction on gatherings	99	0
International support	108	0
Investments in vaccines	116	0
Vaccination policy	118	1
Public information campaigns	123	0

(b) New Deaths.		
Target: New Confirmed per 100.000		
Feature	**Global Ranking Score**	**Times in First 5 Positions**
Facial coverings	38	3
Driving	40	2
Stay at home requirements	41	2
Residential	44	1
Workplaces closing	44	2
Workplaces	47	1
Walking	48	1
Retail and recreation	49	1
Restriction on internal movement	51	1
Transit	52	1
Vaccination policy	60	1
Grocery and pharmacy	62	0
Public transport closing	64	2
Parks	65	1
School closing	70	1
Transit station	73	0
Debt relief	78	1
Emergency investments in healthcare	82	1
Income support	82	1
Testing policy	83	1
Restriction on gatherings	90	0
International travel control	96	0
Contact tracing	97	1
International support	107	0
Fiscal measures	111	0
Cancel public events	114	0
Investments in vaccines	114	0
Public information campaigns	128	0

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