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COVID-19 DATA RELIABILITY RANKING OF COUNTRIES WITH GREY RELATIONAL ANALYSIS AND BENFORD'S LAW

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Abstract

The covid-19 disease has become a pandemic that spreads at an unexpected pace around the world. There are more than 450 million cases and 6 million deaths worldwide at the start of March 2022. Benford's law is a statistical technique that serves to determine whether data fraud has been committed in a data structure that uses repetitive numbers. In this study, 18 countries with more than 5 million cases worldwide were ranked using grey relational analysis with the help of Benford's law, an effective method of data fraud. 18 countries are listed separately for 2 years of data with the help of the grey relational analysis method and Benford's analysis results. According to the results of the study, it was determined that some countries showed changes in data reliability between 2020 and 2021. It has been determined that the data of Germany, France, and the Netherlands are the most reliable.

Key Words: *Benford's Law, Grey Relational Analysis, Data Fraud, Covid-19*

GRİ İLİŞKİSEL ANALİZ VE BENFORD YASASI YARDIMIYLA ÜLKELERİN COVID-19 VERİ GÜVENİRLİĞİ SIRALAMASI

Öz

Covid-19 hastalığı, dünya çapında beklenmedik bir hızla yayılan ve pandemi olarak ilan edilen küresel bir hastalıktır. Mart 2022'nin başında dünya çapında 450 milyondan fazla vaka ve 6 milyondan fazla ölüm rapor edilmiştir. Benford yasası, tekrarlayan sayıları kullanan bir veri yapısında veri sahtekârlığı yapılıp yapılmadığını belirlemeye yarayan istatistiksel bir tekniktir. Bu çalışmada, etkin bir veri sahtekârlığı yöntemi olan Benford yasası yardımıyla dünya genelinde 5 milyondan fazla vakaya sahip 18 ülke gri ilişkisel analiz kullanılarak veri sahteciliğine göre sıralanmıştır. Gri ilişkisel analiz yöntemi ve Benford analizi sonuçları yardımıyla 2 yıllık veriler için 18 ülke ayrı ayrı listelenmiştir. Çalışmanın sonuçlarına göre bazı ülkelerin 2020 ile 2021 yılları arasında veri güvenirliğinde değişiklik gösterdiği belirlenmiştir. En güvenilir verilerin Almanya, Fransa ve Hollanda olduğu belirlenmiştir.

Anahtar Kelimeler: *Benford Yasası, Gri İlişkisel Analiz, Veri Sahtekârlığı, Covid-19*

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1. Introduction

Coronaviruses (CoV) are known as a large family of viruses that cause a variety of diseases, from colds to severe respiratory failure to more serious diseases such as MERS-CoV, and SARS. While many subtypes of coronaviruses have caused colds in humans, on December 31, 2019, a new type of coronavirus was found to cause disease in humans in Wuhan, Hubei province, China, and the name of the disease was adopted as Covid-19. Because there was insufficient information about the newly identified Covid-19 virus, there were difficulties in its treatment, and the disease spread rapidly. Because the disease has spread across continents and has reached serious heights in many countries, the World Health Organization has considered this epidemic a "pandemic". It is defined as the pandemic of the 21st century. At the beginning of March 2022, more than 450 million patients and more than 6 million deaths were reported worldwide due to this disease (WHO, 2022). Since statistics is one of the most important auxiliary tools in fighting the disease, it is thought that all countries of the world show the necessary sensitivity to this issue. However, although the data is increasing day by day, speculative statements about the data are coming from many countries. The voices of groups claiming that real data are stored, reduced, or changed are getting more and more effective every day. Is it possible to prove this kind of data fraud? Probably it is not easy to answer this question. Nevertheless, it is possible to detect data fraud with statistical methods such as Benford's law and the chi-square goodness of fit test. Benford's law states that the numbers in the specified digit in a series of numbers must occur with certain probabilities. In this way, how much the researched number series deviates from the specified probabilities and the reasons for this can be found.

With this study, it is aimed to rank 18 countries in the world with more than 5 million Covid-19 cases until March 2022 in terms of data fraud. Of the countries that make up the data set used in the study, 50% are in Europe, 28% are in America, and 22% are in Asia continental. In the calculations made with Grey Relational Analysis, the number of cases and deaths of the countries and the d* and Mean Absolute Deviation (MAD) values obtained by the Benford law digit test results were used as variable inputs. With the help of the values obtained, countries with more than 5 million Covid-19 cases are ranked for the years 2020 and 2021 and 2020-2022 period.

2. Benford's Law

Some of the frauds in the economic world are based on transformed data (Nye and Moul, 2007). In this case, detecting the transformation of the data also means revealing the fraud. With Benford's law, such tricks can be detected. Benford's law in short expresses that the probability of finding numbers in the digits of the numbers forming a naturally formed number sequence is not equal. When we consider a series of randomly formed numbers in real life, the probability that the first digit of the number is 1 is not the same as that of a 9. Benford's law defends that the probability of the first digit being 1 is almost 6 times greater than the probability of being 9 (Nigrini, 2012).

This method was firstly discovered (Newcomb, 1881). He observed that tables of logarithms were used more often for smaller digits than for larger ones. 57 years later, Benford expanded on the same study again (Benford, 1938). Looking at the population statistics of cities, he noticed again that many more of the numbers start with "*1*" than any number. He continued to investigate this, and when he looked at stock prices, River lengths, sports statistics, and many other collections of numbers, he encountered the same interesting results. The digits of these data could be closely defined by the logarithmic distribution.

The main numerical analysis tests prepared based on Benford's Law are First Digit Test, Second Digit Test, First Two-Digit Test, First Three-Digit Test, Repeated Numbers Test, and Last Two-Digit Test. The first Digit test is the main test of numerical analysis. This test is a suitability test, and it is a very general formula given in Equation.1:

$$P\left(d\right) = \log(d+1) - \frac{\log(d)}{\log(10)} - \log(1) = \log\left(\frac{d+1}{d}\right) \tag{1}$$

According to the formula, the probability that a number's first digit is "*1*" is 0.301, while a "*9*" is expected with a much lower probability of 0.046. In Table.1 probabilities predicted by Benford's Law for the first and higher-order digits are given.

Table 1: First, Second, Third, and Fourth Digit Proportions of Benford's Law

d_i	$P(d_1)$	$P(d_2)$	$P(d_3)$	$P(d_4)$
0		0.11968	0.10178	0.10018
1	0.30103	0.11389	0.10138	0.10014
2	0.17609	0.10882	0.10097	0.10010
3	0.12494	0.10433	0.10057	0.10006
4	0.09691	0.10031	0.10018	0.10002
5	0.07918	0.09668	0.09979	0.09998
6	0.06695	0.09337	0.09940	0.09994
7	0.05799	0.09035	0.09902	0.09990
8	0.05115	0.08757	0.09864	0.09986
9	0.04576	0.08500	0.09827	0.09982

Source: Nigrini, MJ, A Taxpayer Compliance Application of Benford's Law, 1996.

Although there is no definite information about the minimum size of the data set to which the Benford analysis will be applied, it is known that it gives successful results in data sets with large observations. The general rule is that the data set should have at least 1,000 records before we should expect good conformity to Benford's Law. Another general rule is not to test the first-two digit frequencies of data sets with fewer than 300 records. The first digit test (with all its flaws) should be used on small data sets. For data sets with fewer than 300 records, the records can simply be sorted from largest to smallest and the pages visually scanned for anomalies (Nigrini, 2012).

There are some suggestions for the suitability of the data for Benford analysis in small-observation datasets. One of the most frequently used ones is the chi-square test and the graphical examination of whether the observation values ordered from the smallest to the largest are following the logarithmic distribution (Miller, 2015). The geometric foundation of Benford's Law means that a data set will have Benford-like properties if the ordered (ranked from smallest to largest) records closely approximate a geometric sequence (Nigrini, 2012).

The nonmathematical guidelines for determining whether a data set should follow Benford's Law can be given as four steps:

i. The records should represent the sizes of facts or events.

ii. There should be no built-in minimum or maximum values for the data, except perhaps for a minimum of 0 for data that can only be made up of positive numbers.

iii. The records should not be numbers used as identification numbers or labels.

iv. Another consideration is that there are more small records than large records in the data table (Nigrini, 2012).

Tests of significance for Benford's Law require that the "*true*" distribution must follow exactly the Benford distribution. Our null hypothesis is that the observed or calculated distribution follows the theoretical or expected (Benford) distribution. The most common test is the Chi-Square test of Goodness of Fit (Koch and Okamura, 2020). For the first digit test Equation 2 can be used:

$$D^2 = n\sum_{d=1}^{9}\frac{\left(H_d - P_d\right)^2}{P_d} \quad (2)$$

and for second and other digit tests it can be used with Equation 3:

$$D^2 = n\sum_{d=0}^{9}\frac{\left(H_d - P_d\right)^2}{P_d} \quad (3)$$

where n denotes the number of observations, H is the observed frequencies of the digits and P is Benford's Law distribution. Another measure used for a data set's non-conformance to Benford's law, d*, was introduced by (Cho and Gaines, 2007):

$$d^* = \frac{\sqrt{\sum_{d=1}^{9}\left(\tilde{P}(d) - P(d)\right)^2}}{1.03606} \quad (4)$$

where d is the first digit from 1 to 9 and $\tilde{P}(d)$ stands for the probability distribution of each first digit in real datasets and 1.03606 is the maximum distance (used for normalization). For a data set that conforms to Benford's law, d* = 0.0; for a data set that is as non-conforming as possible, d* = 1.0. Goodman (2016) proposed that a d* higher than 0.25 is high evidence of data manipulation.

Another test used to determine the mismatch in Benford's Law is Mean Absolute Deviation (MAD). MAD is a test used to assess the content of a data set's similarity to Benford's Law, which is independent of the size of the data set being regarded. The first digit test is generally used as the first important level and the second digit test is usually used as a secondary important level test of acceptability. Different tests defined in the literature are used to test the goodness of fit of Benford's Law. The lower the MAD value, it is understood that the average difference between real and expected rates is so small (Drake and Nigrini, 2000).

$$MAD = \sum_{i=1}^{K} \frac{|AP - EP|}{K} \quad (5)$$

In the MAD formula K represents the number of bins, AP denotes the actual proportion, and EP is the expected proportion. Yet the lower the MAD means the lower the average difference will be, but there are no solid methods for decision-making. Nigrini (2012) has provided some guidelines for determining critical scores and ranges to test compliance with Benford law, based on their personal experience. The adjusted Mean Absolute Deviation critical value ranges are shown in Table 2.

Table 2: Mean Absolute Deviation Critical Value Ranges

Conformity Range	First Digits	Second Digits	First Two Digits
Close Conformity	0.000-0.006	0.000-0.008	0.0000-0.0012
Acceptable Conformity	0.006-0.012	0.008-0.010	0.0012-0.0018
Marginally Acceptable Conformity	0.012-0.015	0.010-0.012	0.0018-0.0022
Nonconformity	Above 0.015	Above 0.012	Above 0.0022

For MAD values to be interpreted within these ranges, the observation values used in the analysis must be large enough. In literature, the use of Benford's Law is used to detect fraud which has been widely demonstrated in many areas. Gonzales-Garcia and Pastor (2009) used Benford's law for economic data quality, Rausch et al. (2011) investigated fraud in public statistics and Holz (2014) reported China's GDP statistics quality with Benford's Law. Carslaw (1988) and Berton (1955) used the Benford method in financial research studies. Wei and Vellwock (2020) tested the accuracy of the covid case numbers of selected countries. Hill (1995) and Schafer et al. (2004) studied the significance of Benford's law according to various steps. Buck et al. (1993) studied the values of the 477 radioactive half-lives of unhindered alpha decays that were accumulated throughout the past century. They found that vary over many orders of magnitude, found that the frequency of occurrence of the first digits of both measured and calculated values of the half-lives is in "*good agreement*" with Benford's law. Ley (1996) found that "*the series of one-day returns on the Dow-Jones Industrial Average Index (DJIA) and the Standard and Poor's Index (S&P) reasonably agrees with Benford's law*". Costas et al. (2008) observed that in a certain cyanobacterium, *"the distribution of the number of cells per colony satisfies*

Benford's law". Docampo et al. (2009) reported that "*gross data sets of daily pollen count from three aerobiological stations (located in European cities with different features regarding vegetation and climatology) fit Benford's law*".

With the start of the Covid-19 pandemic, countries began to publish daily cases and death numbers caused by this disease. Many researchers have also investigated whether the data published by the countries comply with the Benford law, and thus whether the countries commit data fraud. Koch and Okamura (2020) demonstrated that the USA, Italy, and China's Covid-19 confirmed cases numbers match the Law, showing high Benfordness and no data manipulation for these countries. Idrovo and Manrique-Hernández (2020), likewise proved no data manipulation on China's numbers. Sambridge and Jackson (2020) suggested that Covid-19 data till April 2020 from the United States, Japan, Indonesia, and most European countries follow well the distribution, but also suggested anomalies. Raul (2020) indicated that Italy, Portugal, Netherlands, the United Kingdom, Denmark, Belgium, and Chile may have altered Covid-19 data, in a large study of 23 countries. Since all these studies were conducted with few observations, they showed that the Covid-19 data can be seen from the perspective of Benford, although they have a question mark as to whether the Benford results are reliable.

3. Grey Relational Analysis

Grey System Theory was developed by Deng (1982) as a new system and focused on the direction of the relationship of two or more components based on the unknown. This method is preferred for grouping variables, especially when the sample size is small and the sample distribution is unknown (Feng and Wang, 2000:136). The term "*grey*" here refers to incomplete or no knowledge of information. The similarities or differences between two elements or two subsystems within a particular system are called "*Grey relations*". The method used to measure the developments in the degree of changes in the similarities and differences between the elements can be summarized as Grey Relational Analysis. This method allows determining the degree of relationship between each factor in a grey system and the compared factor (reference) series. Each factor is defined as a sequence. The degree of influence between the factors is called the grey relational degree (Feng and Wang, 2000). It is possible to examine the research and application methodology of Grey System Theory under six main headings. These titles are grey production, grey relational analysis, grey modeling, grey decision making, grey control, and grey prediction (Kose et al., 2011). The Grey relational analysis consists of six steps (Zhai et al., 2009:7076). These can be listed as grey production, grey relational analysis, grey modeling, grey decision making, grey control, and grey prediction. The steps of the grey relational analysis method can be given in 6 steps (Wu, 2002):

***Step 1**:* Creating the decision matrix

$$X_i = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_n(1) & x_n(2) & \cdots & x_n(n) \end{bmatrix}$$

***Step 2**:* Creating the comparison matrix

Reference series can be defined as $x_0 = \left(x_0(1), x_0(2), ..., x_0(j), ..., x_0(n)\right)$

In $x_0(j)$; j shows the largest (or lowest) value among the normalized values of the criterion. The comparison matrix is created by writing the reference series in the first row of the decision matrix.

***Step 3**:* Normalization process and creation of the normalization matrix

In this step, the data set is normalized. Normalization processes are carried out to bring the data with different units and sizes to the same standard. Three possible situations can be encountered here: benefit, cost, and optimal situation.

Benefit situation $x_i^* = \dfrac{x_i(j) - \min\limits_j x_i(j)}{\max\limits_j x_i(j) - \min\limits_j x_i(j)}$

Cost situation $x_i^* = \dfrac{\max\limits_j x_i(j) - x_i(j)}{\max\limits_j x_i(j) - \min\limits_j x_i(j)}$

Optimal situation $x_i^* = \dfrac{\left|x_i(j) - x_{0b}(j)\right|}{\max\limits_j x_i(j) - x_{0b}(j)}$

After these operations, the decision matrix in Step 1 becomes as:

$$X_i^* = \begin{bmatrix} x_1^*(1) & x_1^*(2) & \cdots & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & \cdots & x_2^*(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_n^*(1) & x_n^*(2) & \cdots & x_n^*(n) \end{bmatrix}$$

***Step 4**:* Creating the absolute value table

$$\Delta_{0i}(j) = \left|x_0^*(j) - x_i^*(j)\right|$$

***Step 5**:* Creating the grey relational coefficient matrix

$$\gamma_{0i}(j) = \frac{\Delta \min + \xi \Delta \max}{\Delta_{0i}(j) + \xi \Delta \max}$$

Here ξ is the distinguish coefficient which is usually taken as 0.5.

Step 6: Calculating the degree of relationship

$$\Gamma_{0i} = \frac{1}{n}\sum_{j=1}^{n}\gamma_{0i}(j)$$

In this formula, the criteria are assumed to be of equal importance. By assigning different weights to the criteria, the weighted correlation degree matrix is calculated (Kuo et al., 2008).

4. Application

In the application part, the Covid-19 data reliability rankings of the countries were made with grey relational analysis. The elements of the input matrix to be used in the grey relational analysis were calculated with the help of the values obtained from the Benford analysis. In the first stage of the analysis, the first 3 digits of the number of cases and deaths for each country were subjected to the Benford analysis separately and the d* and MAD values were calculated. Then, d* and MAD values calculated separately for two different years formed the elements of the input matrix in the grey relational analysis. Finally, with the help of the input matrix, the grey relational ranking was made, and the final ranking of the countries was determined. In all applications, data obtained from the web address of the World Health Organization was used (WHO, 2022). The data which contains the numbers of cases and deaths of Covid-19 from 18 countries are described between 03.01.2020 and 03.01.2022. Selected countries are those with more than 5 million cases of Covid-19 as of March 2022. The entire data set used in the study consists of 730 observations for each country. Accordingly, all data for the first year were taken between 1 March 2020 and 28 February 2021, and for the second year between 1 March 2021 and 28 February 2022.

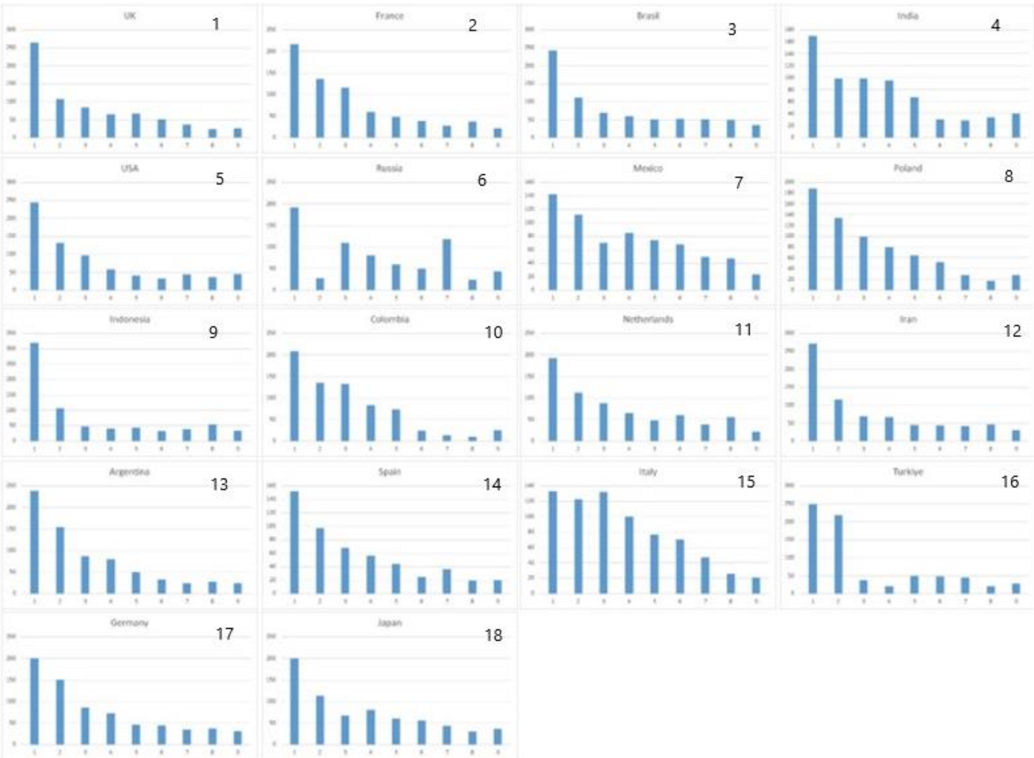
Testing of Suitability of Data for Benford's Law

The main purpose of the study is to rank the countries with more than 5 million Covid-19 cases using the grey relational method, with the help of grey numbers to be obtained with the help of Benford analysis. In this subsection, however, how much of the data is suitable for Benford analysis is tested. According to the chi-square analysis, the UK, Russia, Indonesia, Netherlands, Iran, Turkey, and Mexico data on the number of Covid-19 cases were found to be statistically insignificant ($p>0.05$). Similarly, data from India, Russia, Mexico, Colombia, Italy, and Turkey were found to be statistically insignificant in the number of Covid-19 deaths ($p>0.05$). In Figure 1 and Figure 2, the graphs of the Benford distributions of the data are given. We can conclude similar results looking at Figure 1 and Figure 2.

Figure 1: Benford Distribution of Covid-19 Case Numbers by Countries

Note: 1:USA, 2:India, 3:Brazil, 4:Spain, 5:France, 6:UK, 7:Russia, 8:Argentina, 9:Iran, 10:Colombia, 11:Indonesia, 12:Netherland, 13:Poland, 14:Mexico, 15:Japan, 16:Germany, 17:Turkey, 18:Italy

Figure 2: Benford Distribution of Covid-19 Death Numbers by Countries



Note: 1:UK, 2:France, 3:Brazil, 4:India, 5:USA, 6:Russia, 7:Mexico, 8:Poland, 9:Indonesia, 10:Colombia, 11:Netherland, 12:Iran, 13: Argentina, 14:Spain, 15:Italy, 16:Turkey, 17:Germany, 18:Japan

In Table 3, 2020 results for d* and MAD values are given for the first digit, second digit and third digit of Benford's test according to both Covid-19 case and death numbers. Values that are insignificant according to Chi-square analysis are shown with (*) in the d* column (p<0.05).

Table 3: 2020 Results of the Digits Test for d* and MAD

Countries	Case	d*			MAD		
		1st digit	2nd digit	3rd digit	1st digit	2nd digit	3rd digit
USA	Case	0.119*	0.041	0.043	0.032	0.010	0.013
	Death	0.101*	0.070*	0.055	0.026	0.019	0.017
India	Case	0.069*	0.053	0.045	0.018	0.013	0.011
	Death	0.100*	0.096*	0.061	0.026	0.027	0.015
Brazil	Case	0.174*	0.059	0.021	0.052	0.018	0.006
	Death	0.153*	0.081*	0.065	0.042	0.023	0.018
France	Case	0.060	0.051	0.043	0.016	0.015	0.012
	Death	0.061	0.036	0.062	0.018	0.011	0.017
UK	Case	0.032	0.038	0.044	0.009	0.011	0.013
	Death	0.055	0.046	0.058	0.015	0.014	0.015
Russia	Case	0.156*	0.076*	0.035	0.045	0.020	0.008
	Death	0.182*	0.051	0.027	0.055	0.015	0.007
Germany	Case	0.046	0.057	0.062	0.013	0.016	0.017
	Death	0.041	0.047	0.069*	0.012	0.013	0.020
Turkey	Case	0.188*	0.067	0.106*	0.051	0.018	0.022
	Death	0.142*	0.085*	0.070*	0.037	0.021	0.016
Italy	Case	0.142*	0.057	0.050	0.037	0.014	0.012
	Death	0.135*	0.061	0.031	0.035	0.016	0.008
Spain	Case	0.039	0.210*	0.188*	0.011	0.041	0.038
	Death	0.101*	0.212*	0.224*	0.030	0.041	0.043
Argentina	Case	0.148*	0.089*	0.047	0.043	0.026	0.013
	Death	0.102*	0.061	0.057	0.026	0.016	0.016
Iran	Case	0.192*	0.073*	0.040	0.050	0.017	0.011
	Death	0.134*	0.077*	0.061	0.034	0.019	0.017
Netherlands	Case	0.141*	0.035	0.025	0.042	0.009	0.006
	Death	0.080*	0.054	0.065	0.021	0.015	0.019
Colombia	Case	0.160*	0.065	0.047	0.047	0.018	0.015
	Death	0.203*	0.105*	0.056	0.063	0.029	0.013
Indonesia	Case	0.093*	0.066*	0.067*	0.026	0.017	0.018
	Death	0.104*	0.043	0.022	0.029	0.012	0.006
Poland	Case	0.124*	0.057	0.043	0.027	0.017	0.011
	Death	0.052	0.056	0.040	0.013	0.015	0.010
Mexico	Case	0.158*	0.051	0.046	0.046	0.012	0.013
	Death	0.125*	0.032	0.045	0.039	0.009	0.012
Japan	Case	0.114*	0.054	0.051	0.027	0.015	0.014
	Death	0.074*	0.047	0.061	0.022	0.014	0.018

Since all d* values were below the critical value (0.25) in all 3 kind of digit tests, we can conclude that there is no significant data fraud. When we look at the results in Table 3 in general, it is seen that the death of case numbers in 15 of 18 countries are statistically insignificant according to the chi-square test. It is seen that the first digit, second digit and third digit tests of the case and death data of only 2 countries, France, and the UK, are significant. In Germany, the third-digit death data were insignificant, and the others were found to be significant. It is concluded that Spain and Turkey's death numbers, and Indonesian case numbers, have problematic results in all three of digit tests.

When we evaluate the MAD results in Table 3 according to the MAD ranges given in Table 2, it is seen that no country's data (for both case and death) is in the range of "*Close conformity*" and "*Acceptable conformity*" according to the first digit results. The case numbers of the UK and Spain, and the death numbers of Germany are only in the range of "*Marginally acceptable conformity",* while the data of other countries are defined as "*Nonconformity".* According to the second digit results, only France and Mexico death numbers, and USA and UK case numbers were in the "*Acceptable conformity"* range. In Table 4, 2021 results for d* and MAD values are given for the first digit, second digit and third digit of Benford's test according to both Covid-19 case and death numbers.

It is seen that the all-digit tests of the case and death data of only 1 country, the USA, are significant. Spain has significant first-digit results, but 2nd and 3rd digit results are insignificant as well. Only Mexico's death numbers are insignificant in all three tests. When we look at the d* analysis, it is seen that only Russia's death numbers are above the critical value of d*. It can be said that these data are not reliable. In addition, it is seen that the number of deaths in Indonesia, Colombia, and Turkey and the number of cases in the UK are very close to the critical value. It is seen that the MAD values of 2021 are higher than those of 2020. As a result, all values can be evaluated as "*Nonconformity*" in the first digit test.

In the second part of the analysis, 18 countries were ranked in terms of data fraud according to the Benford digit analysis results. For this, the grey relational analysis method and the first digit, second digit and third digit results obtained from the Benford analysis for case and death numbers of 18 countries were used.

When we look at the results in Table 5, it is seen that the most reliable data belong to Germany, France, and the Netherlands. It is remarkable that the UK data, which was in first place in 2020, dropped to 12th place in 2021, and the USA data, which was in 9th place in 2020, rose to 2nd place in 2021. Especially in 2021, Spain, which did not disclose weekend data, is at the bottom of the list. Turkey, Colombia, and Russia are other lower-ranked countries.

Table 4: 2021 Results of the Digits Test for d* and MAD

Countries	Case	d*			MAD		
		1st digit	2nd digit	3rd digit	1st digit	2nd digit	3rd digit
USA	**Case**	0.0643	0.0503	0.0484	0.0169	0.0131	0.0131
	Death	0.0597	0.0634	0.0414	0.0166	0.0144	0.0113
India	**Case**	0.0982	0.0405	0.0483	0.0260	0.0113	0.0140
	Death	0.1830*	0.0416	0.0367	0.0492	0.0123	0.0095
Brazil	**Case**	0.1142*	0.0479	0.0543	0.0308	0.0130	0.0150
	Death	0.0904*	0.0433	0.0312	0.0204	0.0105	0.0084
France	**Case**	0.1169*	0.0410	0.0596	0.0304	0.0115	0.0160
	Death	0.0544	0.0509	0.0448	0.0144	0.0139	0.0118
UK	**Case**	0.2303*	0.0426	0.0494	0.0576	0.0105	0.0126
	Death	0.1283*	0.0493	0.0493	0.0275	0.0135	0.0143
Russia	**Case**	0.2086*	0.0505	0.0454	0.0656	0.0133	0.0117
	Death	0.3411*	0.1193*	0.0552	0.0921	0.0336	0.0145
Germany	**Case**	0.0502	0.0350	0.0578	0.0140	0.0102	0.0153
	Death	0.1112*	0.0381	0.0462	0.0225	0.0105	0.0113
Turkey	**Case**	0.2143*	0.0596	0.0578	0.0519	0.0158	0.0153
	Death	0.2435*	0.0438	0.0801*	0.0567	0.0114	0.0229
Italy	**Case**	0.0502	0.0366	0.0578	0.0142	0.0086	0.0173
	Death	0.1715*	0.0385	0.0452	0.0407	0.0091	0.0112
Spain	**Case**	0.0673	0.2919*	0.2932*	0.0195	0.0571	0.0573
	Death	0.0777	0.2976*	0.2952*	0.0162	0.0577	0.0575
Argentina	**Case**	0.1206*	0.0438	0.0617	0.0313	0.0128	0.0149
	Death	0.0642*	0.0634	0.0467	0.0182	0.0181	0.0134
Iran	**Case**	0.1302*	0.0635	0.0361	0.0374	0.0146	0.0088
	Death	0.0600	0.0371	0.0413	0.0162	0.0108	0.0106
Netherlands	**Case**	0.1278*	0.0528	0.0366	0.0360	0.0143	0.0095
	Death	0.0487	0.0430	0.0600	0.0140	0.0120	0.0167
Colombia	**Case**	0.2140*	0.0715	0.0396	0.0596	0.0155	0.0113
	Death	0.2155*	0.0621	0.0621	0.0624	0.0171	0.0178
Indonesia	**Case**	0.1828*	0.0369	0.0614	0.0474	0.0107	0.0150
	Death	0.2266*	0.0609	0.0578	0.0497	0.0154	0.0133
Poland	**Case**	0.0982*	0.0190	0.0415	0.0293	0.0046	0.0103
	Death	0.1187*	0.0479	0.0740*	0.0340	0.0124	0.0179
Mexico	**Case**	0.0559	0.0969*	0.1016*	0.0165	0.0221	0.0205
	Death	0.1181*	0.0757*	0.0970*	0.0275	0.0165	0.0204
Japan	**Case**	0.0645	0.0410	0.0762*	0.0163	0.0116	0.0222
	Death	0.0560	0.0705*	0.0738*	0.0150	0.0200	0.0216

Table 5: Covid-19 Data Reliability Rankings of Countries

Rank	2020 Data	Rank	2021 Data	Rank	Whole Data
1	UK	1	Germany	1	Germany
2	Germany	2	USA	2	France
3	France	3	Italy	3	Netherlands
4	Poland	4	Iran	4	Poland
5	Netherlands	5	Netherlands	5	USA
6	Indonesia	6	France	6	Japan
7	Japan	7	Brazil	7	UK
8	Mexico	8	Japan	8	Italy
9	USA	9	Poland	9	India
10	India	10	India	10	Brazil
11	Italy	11	Argentina	11	Iran
12	Russia	12	UK	12	Argentina
13	Brazil	13	Mexico	13	Indonesia
14	Argentina	14	Indonesia	14	Mexico
15	Iran	15	Colombia	15	Russia
16	Colombia	16	Turkey	16	Colombia
17	Turkey	17	Russia	17	Turkey
18	Spain	18	Spain	18	Spain

5. Conclusion

According to the analysis, it was concluded that the difference between the frequency of Covid-19 Case Records officially declared by countries and Benford's theoretical probabilities - although some countries are close to d* boundary values - could be considered randomly. In some studies, conducted by mid-2020, there were criticisms that the Covid-19 data for some countries did not reflect the truth (Koch and Okamura, 2020; Lee et al., 2020). However, this difference can be said to be even more acceptable compared to mid-2020 data. An increase in the number of observations and efforts by countries to explain data more transparently is thought to have been effective in this. In this study, countries with Covid -19 case numbers of more than 5 million were ranked with Grey Relational Analysis based on Benford's test results. The 18 countries that were the subject of the study were ranked according to Benford's analysis. Thus, it was possible to determine which country's data should be more reliable, and which should publish more careful results. While the Covid-19 pandemic affected countries and societies, countries closed their borders to ensure their isolation, the right to free movement was interrupted, sociocultural interaction was restricted, the height of the number of people infected or killed by the spread of the disease led to a re-questioning of an era called modern, measured by the sophistication of science and technology. By examining the extraordinary and unexpected developments in the history of the world that continue for a certain period, it will be seen that the destructive behavior patterns that manifest themselves in the psychosocial context are not very exceptional. As the most important measure that countries should take, it may be too quick to return to the harsh but determined attitudes made at the beginning of the epidemic and not compromise on the decisions taken.

This article demonstrates that Covid-19 data can also be used in classification and ranking studies. Based on this, a similar ranking of cities in all countries or countries of the world can be made, and analyses of countries or cities with a similar number of cases or deaths can be performed more quickly.

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