

# COVID-19 pandemic: Analyzing of infection waves in Germany in comparison with common infectious diseases by using reliability methods.

Stefan Bracke<sup>a</sup> and Alicia Puls<sup>a</sup>

<sup>a</sup>Chair of Reliability Engineering and Risk Analytics, University of Wuppertal, Germany,  
*bracke@uni-wuppertal.de*

---

**Abstract:** Since December 2019, the world is confronted with the COVID-19 pandemic, caused by the Coronavirus SARS-CoV-2. The COVID-19 pandemic with its incredible spreading speed shows the vulnerability of a globalized and networked world. The first two years of the pandemic were characterized by several infection waves, described by length, peak, and speed. The infection waves caused a heavy burden on health systems and severe restrictions on public life, like educational system shutdown, travel restrictions, limitations regarding public life, or a comprehensive lockdown within a lot of countries. The goal of the presented research study is the analysis of the development of the six dominant infection waves in Germany within the first two years of the COVID-19 pandemic (February 2020 – February 2022). The analyses are focusing on the occurrence of infection and spreading behavior, in detail on attributes like length, peak, and speed of each wave. Furthermore, various impacts of lockdown strategies (hard, soft) or virus variants are considered. The analyses of the infection waves are based on a transfer and application of methods – especially the Weibull distribution model and statistical hypothesis tests – used in reliability engineering for analyzing the upcoming failure development within product fleets in the field. The spreading behavior of a COVID-19 infection wave can be described by the Weibull distribution model in a sound way, related to a short time interval. The interpretation of the Weibull model parameters allows the assessment of the COVID-19 infection wave characteristics and generates additional information to classical infection analysis models like the SIR model [10]. Finally, the characteristics of the COVID-19 infection waves are analyzed in the context of other common infectious diseases in Germany like Influenza or Norovirus. This study continues previous research; cf. [1–3,11,12].

---

## 1. INTRODUCTION

In December 2019, the world was confronted with the outbreak of the respiratory disease COVID-19 (“Corona”) caused by Coronavirus SARS-CoV-2. The first confirmed infection was detected in the City of Wuhan, Hubei, China. This was the start of the COVID-19 epidemic in China. In the first quarter of 2020, it evolved into a worldwide pandemic.

In the subsequent following time of two years up to today (04/2022), the COVID-19 pandemic challenged the globalized world. The impact on health systems, social life, and the restrictions on public life respectively lockdown (with different characteristics) have defined life in many countries.

COVID-19 is an infectious disease affecting the respiratory tract. The virus occurs worldwide, even in hot countries, and shows a seasonal impact. The expansion of the Coronavirus is characterized by waves, distinguished by level, length and peak.

In comparison to other infectious diseases, like Influenza, Norovirus, and Campylobacter enteritis, the spreading speed of the COVID-19 waves is higher and as an indirect consequence, the number of cases is on a higher level.

This paper focuses on analyzing the spreading behavior of the different COVID-19 pandemic waves in Germany (first confirmed case 01-27-2020) in the first two years of the pandemic (data status 03-10-2022). Up to this point in time, Germany was confronted with six main waves. The characteristic of the waves depends on many factors: One of the main influencing factors regarding the wave’s characteristic is the lockdown type and the set of accompanying measures. Therefore, in this paper, the impact of different lockdown measures is evaluated. Furthermore, a comparison to the well-known infectious diseases, Influenza, Norovirus, and Campylobacter enteritis is done.

The shown analysis is based on an application transfer of reliability engineering methods, which allows a comprehensible interpretation of the results.

This paper is the continuation of previous research studies, cf. [1–3,11,12], where the focus is on a detailed evaluation of the characteristics of COVID-19 spreading behavior in the different pandemic phases in Germany and other countries like Japan, Italy, Sweden, Denmark, Iceland, Ireland. The analyses and results shown in this paper build on the research previously conducted.

## 2. GOAL OF RESEARCH STUDY

The overarching goal of the research study is the analysis of the development of the occurrence of infection of COVID-19 in the first two years of the pandemic (02/2020 to 02/2021) in Germany with the use of reliability engineering methods. The detailed goals are as follows:

1. Comparison of the spreading behavior in the six main waves,
2. Analyses of the lockdown impact, considering different lockdown characteristics,
3. Analyses of the infectiousness of COVID-19 in different pandemic phases with other already well-known infectious diseases.

These topics are discussed based on Germany as a reference country for the occurrence of infection in Europe. The reference country is selected due to data quality and access and the different lockdown characteristics. The COVID-19 spreading behavior is compared with the most frequently occurring notifiable infectious diseases in Germany, Influenza, Norovirus, and Campylobacter enteritis.

## 3. METHODS: Fundamentals and application

This section shows the statistical fundamentals for analyzing and comparing the COVID-19 pandemic waves in Germany. The spreading behavior in the different pandemic waves and the impact of measures like lockdown are analyzed by using the Weibull distribution model, cf. Sec. 3.1. The transfer of the application of the Weibull model, which is usually used in reliability engineering, regarding the modeling of infection occurrence is explained in Sec. 3.2. For differentiation of waves within the pandemic the Cox and Stuart trend significance test is used, cf. Sec. 3.3. The basis for Sec. 3 are [3] and [12].

### 3.1 Weibull distribution model

The two-parameter Weibull distribution model is given based on Eq. (1), cf. [17].

$$F(x) = 1 - \exp\left(-\left(\frac{x}{T}\right)^b\right) \quad (1)$$

The parameters, besides the term life span variable  $x$ , are scale parameter  $T$  (location parameter) and shape parameter  $b$ . By using the Weibull model in reliability engineering, the parameters  $T$  and  $b$  can be interpreted as follows: In lifetime analysis the parameter  $T$  represents the characteristic life span. By varying parameter  $b$ , different failure rates can be described, therefore the Weibull model can be flexibly used for different applications, cf. [13]. The shape parameter  $b$  gives hints regarding the character of the failure period: early failure period, random failure, or operation time-related failure behavior. The Weibull parameters are estimated by using the Maximum Likelihood Estimator (MLE), cf. [6].

### 3.2 Transfer: Application of the Weibull model for modeling infection occurrence

The applicability of this distribution model for the analyses of the occurrence of infection is given by the exponential increase in the number of cases of COVID-19. The Weibull distribution model offers the possibility to gain knowledge about the infection development in comparison to classical methods of epidemiology like the SIR model (cf. [10]) or the basic reproduction number. The easy interpretability of the Weibull parameters allows the analysis of the spreading behavior, in particular the spreading speed. The central thinking transfer is the interpretation of the shape parameter  $b$ , the gradient of the Weibull distribution model (log-log-scale), as spreading speed. This is the first advantage

in comparison to the use of an exponential distribution model. The second advantage is the normalization of the Weibull distribution function: It allows easy comparison of measurement data based on different time ranges (samples). Therefore, the Weibull distribution model with the corresponding parameters and probability plots is the base for the comparison of the different COVID-19 waves. [3,12]

For the application of the Weibull distribution model, the data of infection must be ranked by days. The Weibull distribution model requires occurrence times as an input variable; for the infection data, the occurrence time is the reported infection point of time. To avoid a mixture distribution, every pandemic phase like the first wave (increasing case numbers) or the first lockdown (decreasing case numbers) is ranked separately. For comparability, the start day of every pandemic phase is set to “day one” in the data set.

### 3.3 Cox and Stuart trend test

The Cox and Stuart trend test is a non-parametric statistical test for detecting trends in a sample, based on the Binomial distribution. The data is divided in the midpoint into two sequences and the paired difference D is built. For the detection of the second wave, the one-sided form of the test is used to determine an upward trend. Therefore, the number of positive signs in D is defined as S+. The null hypothesis states that S+ follows a binomial distribution with the number of experiments n as the number of elements of D and a probability 0.5. If the p-value of the test is smaller than the significance level alpha, the null hypothesis is rejected and an uptrend is confirmed; cf. [4]:

$$p = P(X \leq S+) = \sum_{k \leq S+} \binom{n}{k} 0.5^k \cdot (1 - 0.5)^{n-k} \leq \alpha \quad (2)$$

For the detection of the different COVID-19 waves the daily confirmed cases are analyzed as a time series. A one-sided trend test (upward trend) is performed with 14 data points and a significance level  $\alpha$  of 0.05, cf. Eq. 2. The tested hypotheses are as follows, cf. [4,11,12]:

- Null hypothesis: There is no upward trend.
- Alternative hypothesis: There is an upward trend (subsequently a starting wave).

The sample size of 14 days is chosen to mitigate outliers and data falsifications, cf. Sec. 5.1. This trend test is repeated until the whole period under review is analyzed. Besides these test decisions, the development of the number of cases is considered for the differentiation of the pandemic waves.

## 4. DATA BASE

In this section, the data base for the analyses and comparison of the different COVID-19 waves is described (Sec. 4.1). Also, uncertainty factors are mentioned and the handling of these data falsification is outlined cf. Sec. 4.2. Elementary definitions – like “confirmed case”, “infection case”, and “hospitalization case” – are explained in [2].

### 4.1 Data base

The base of operations for the presented research study is the infection data documentation of Johns Hopkins University (JHU). In the COVID-19 dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University confirmed cases, recovered cases, as well as death cases regarding countries and regions, are documented, starting at 01-22-2020, cf. JHU (2022) [9]. For this study, the daily confirmed cases from the beginning of 2020 to the beginning of March 2022 were considered.

The data on COVID-19 variants is obtained from the European Centre for Disease Prevention and Control, an EU agency for infectious diseases [5]. The corresponding laboratory sequence data is collected by the Global Initiative on Sharing All Influenza Data in the GISAID EpiCoV data base [8]. For the comparison data of other infectious diseases like Influenza or Norovirus, the data platform SurvStat@RKI 2.0 is used. The Robert Koch Institute (RKI) is the central registration authority for

notifiable diseases in Germany. The number of cases by season week per year can be accessed there for several diseases, cf. [15].

## 4.2 Data Uncertainty

Analytics with respect to pandemic data have to consider several uncertainty factors. This section gives a brief overview of the uncertainty with regard to data acquisition; [12]. A detailed explanation can be found in [2]. Besides the subsequently mentioned uncertainty factors, data and results are to be checked for plausibility.

First of all, the type of measuring method has to be considered. Three aspects are important:

- Criteria for testing (test strategy, e.g., symptom-based or area-wide),
- Reporting system (reporting procedure),
- Accessibility of health department (e.g., weekend-impact).

Furthermore, the spreading behavior is also influenced by the dynamic occurrence of infections and by the handling of the pandemic, besides token lockdown measures. Some of these uncertainty factors are (without claiming to be conclusive):

- Seasonality and climatic effects, cf. [16],
- Mutations of the virus (virus variants),
- Type of treatment, cf. [7] and
- Vaccination progress.

In the present analyses, the uncertainties are taken into account as follows:

- All analyses are carried out focusing on Germany. Uncertainty factors like population density, different definitions of the number of cases, or cultural differences are avoided.
- The data is differentiated between before and after lockdown.
- Ranked data is used and the time is normalized to the date of occurrence.

## 5. DATA ANALYTICS

This section focuses on COVID-19 data analytics. At first, different infection waves in Germany are detected by the Cox-Stuart trend test. An overview of the COVID-19 occurrence of infection is given considering the number of cases and virus variants, cf. Sec. 5.1. In Sec. 5.2, the spreading behavior of six different infection waves is compared. Furthermore, the impact of three lockdown measures on the occurrence of infection is evaluated in Sec. 5.3. Subsequently, the infectiousness of COVID-19 is put into relation to other infectious diseases like Influenza or Norovirus, cf. Sec. 5.4. All analyses are conducted using Weibull distribution models with probability plots and model parameters with confidence belts.

### 5.1 Overview of COVID-19 in Germany

To analyze the different pandemic phases with Weibull distribution models, first, a differentiation of the COVID-19 infection waves has to be made. Therefore, the Cox-Stuart trend test is conducted for the daily confirmed cases in Germany, as described in Sec. 3.3. As a result, the p values (cf. Eq. (2)) are plotted in Figure 1 as black points on the right ordinate. For comparison, the corresponding daily confirmed cases are represented with grey lines on the left ordinate. The corresponding dates are assigned to these values. Additionally, the significance ( $\alpha = 0.05$ ) is shown as a horizontal red line. All points under the red line represent those tests, which result in an upward trend. When the p-value is below the significance level, the null hypothesis is rejected and the alternative hypothesis of an upward trend is assumed as described in Sec. 3.3.

An exponential increase followed by a saturation curve is characteristic of Weibull distribution models. Therefore, the periods under consideration of the infection waves should represent the beginning of these before reaching the peak. Additionally, it is important to recognize the waves as overarching

trends. Therefore, the presence of a series of positive results of the Cox-Stuart trend test is defined as a further criterion for the beginning of the observation period. Considering the overall pandemic trend in Germany, six different infection waves can be identified. The first infection wave as the base for comparison and evaluation of the lockdown impact should represent the unhindered spreading. With the first reported infection case on 01-27-2020 and the beginning of the first lockdown measure in Germany on 03-22-2020, a time span of eight weeks (56 days) results. To ensure comparability, this interval is also set for the other infection waves. The resulting periods under consideration for the six defined waves of infection are plotted as colored vertical lines in Figure 1.

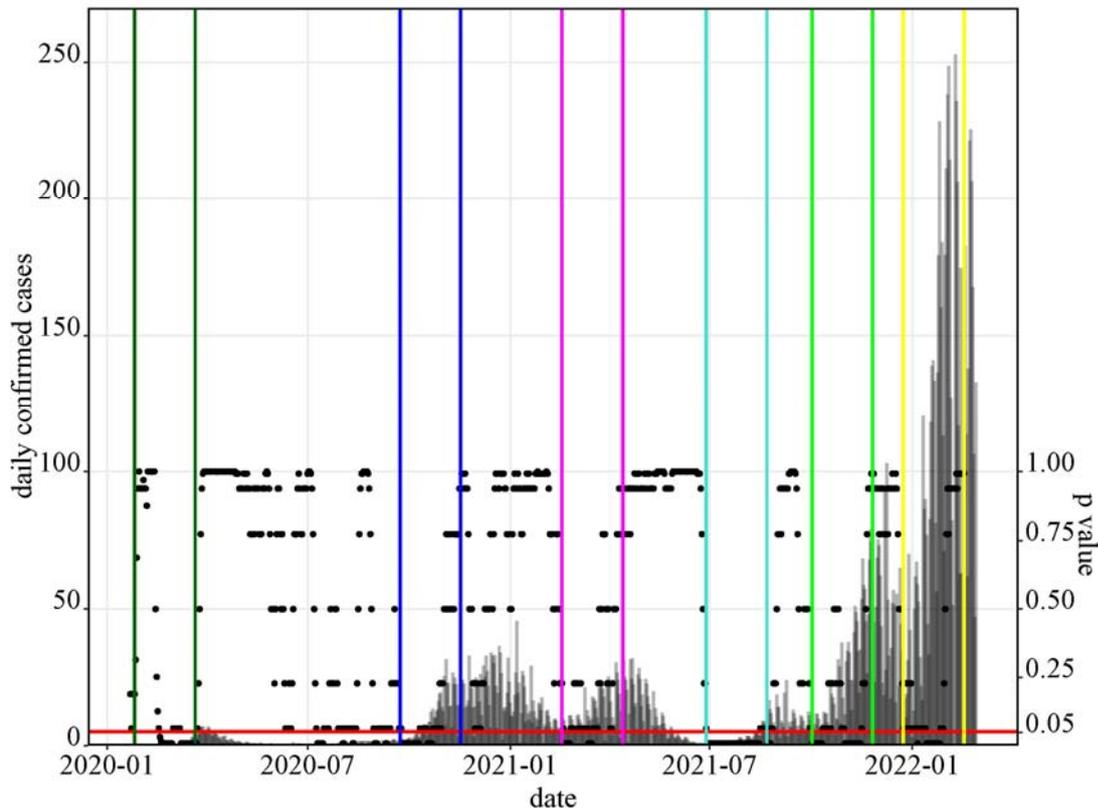


Figure 1: Detection of COVID-19 waves in Germany with Cox-Stuart trend test, p values (black points),  $\alpha=0.05$  (red line), daily confirmed cases (grey lines), periods under consideration for each wave (colored vertical lines).

As addressed in Section 4.2, the different virus variants are an uncertainty factor for the comparison of the pandemic phases. Therefore, in addition to the overview of COVID-19 in Germany, the course of the virus variants is outlined here. In Figure 2 the percentage of the dominant COVID-19 virus variants in Germany per pandemic week is plotted. On a secondary ordinate, the weekly confirmed cases are graphed. In the first year of the pandemic, the wild type of COVID-19 was dominant. From the turn of 2020/2021, the alpha variant, which became known as the British variant, gained in importance. In mid-2021, this variant was replaced by the delta variant, first detected in India. Since the end of 2021 - status beginning of March 2022 - the Omicron variant has been predominant. This variant was first detected in South Africa. The other known virus variants beta (first detected in South Africa) and gamma (first detected in Brazil) never had a significant impact on the occurrence of infection in Germany. The maximum percentage of the beta variant in weekly sequencing was 0.1 %, and 3.6 % for the gamma variant. For this reason, these two variants have been omitted from Figure 2.

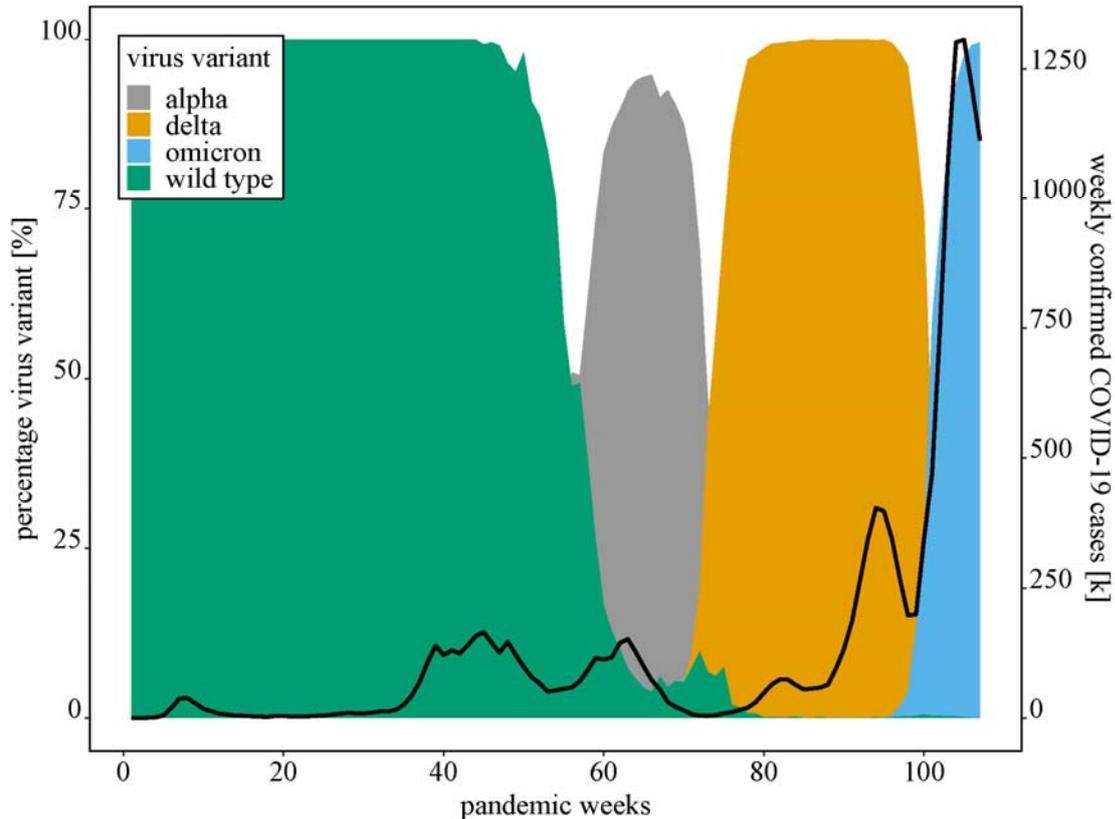


Figure 2: Percentage of predominant virus variants in Germany per pandemic week with weekly confirmed COVID-19 cases.

As can be identified in Figure 2, a relation between the virus variant and the number of cases cannot be established for the wild type as well as for the alpha and delta variants. In contrast, there is a strong positive correlation between the percentage of the virus variant and the number of cases for omicron. For the following analyses of the spreading behavior, this has the consequence that the circumstances and in particular the present virus variant in the periods under consideration have to be considered.

## 5.2 Spreading behavior in different pandemic waves

As a basis for the analyses of the spreading behavior, the key data of the six considered infection waves are documented in Table 1 with the predominant virus variant and the main measures in force during this period.

Table 1: Periods under consideration for each COVID-19 wave in Germany with key dates and characteristics.

Wave	Start date	End date	Predominant virus variant	Main valid measures
1 <sup>st</sup>	01/27/2020	03/21/2020	wild type	none
2 <sup>nd</sup>	09/23/2020	11/17/2020	wild type	community masks
3 <sup>rd</sup>	02/17/2021	04/13/2021	alpha	medical masks, rapid tests
4 <sup>th</sup>	06/28/2021	08/22/2021	delta	medical masks, rapid tests, vaccination campaign
5 <sup>th</sup>	10/02/2021	11/26/2021	delta	medical masks, rapid tests, vaccination campaign, entry to public indoor areas only for vaccinated, recovered or tested
6 <sup>th</sup>	12/24/2021	02/17/2022	omicron	medical masks, rapid tests, vaccination campaign, entrance restrictions for not vaccinated persons

Note: The start dates of the different waves are detected with the Cox-Stuart trend test. The end dates are defined by the period under consideration time span of 56 days of each pandemic phase in the analyses. In every pandemic phase hygiene measures were mandatory.

The analyses of the spreading behavior are made using the two-parameter Weibull distribution model, cf. Sec. 3.1. The shape parameter  $b$  is interpreted as spreading speed. A qualitative evaluation is possible based on a double-logarithmic Weibull probability plot. In this visualization, the Weibull distribution models are plotted as straight lines with the shape parameter  $b$  as slope. The steeper the curve, the higher the shape parameter and thus the higher the spreading speed in the analyzed pandemic phase, cf.[12]. In Figure 3, the Weibull distribution models of the six previously defined infection waves are plotted. For the fifth and sixth waves, every tenth value is plotted due to the high number of cases in these pandemic phases. The fitted Weibull distributions model the spreading behavior well. The deviations between model and data points are in the range of hundredths. The goodness-of-fit value is above 0.95 for all Weibull distribution models in this paper. Explicitly in the barycenter of the infection waves (in which most data points are located due to the exponential course), the Weibull distribution models soundly show the development of the number of cases. Examining Figure 3, one can conclude that in the first COVID-19 infection wave the spreading speed was significantly higher than in the other pandemic phases as the curve is steeper. The spreading speed in the second, fourth, fifth, and sixth waves is on a comparable level. In the third infection wave, the curve is flatter than in the other waves.

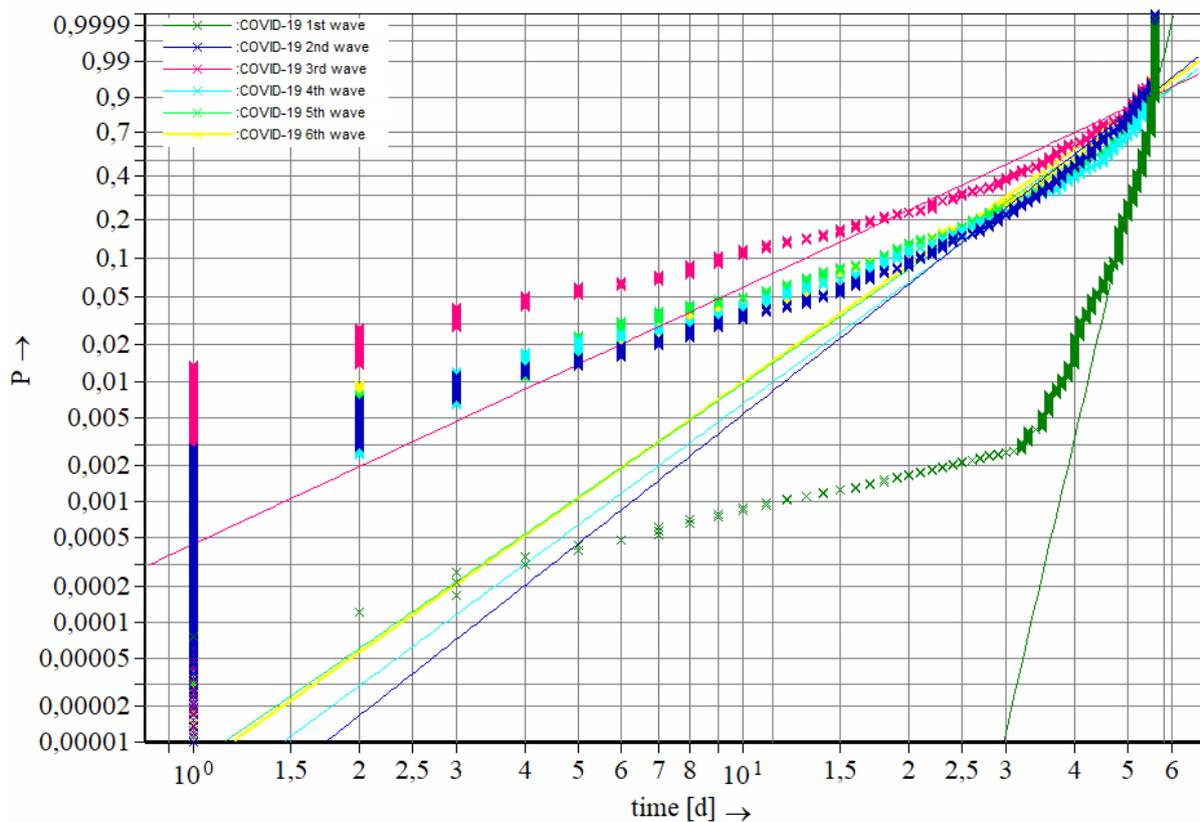


Figure 3: Weibull distribution models COVID-19 in Germany, comparison of different pandemic waves, daily confirmed cases, time span 56 days.

Table 2: Weibull model parameters of different COVID-19 waves in Germany (daily confirmed cases). Confidence level  $\gamma=0.95$ .

Wave	Cases	Scale T [d]	Shape b, confidence belt
1 <sup>st</sup>	22,255	53.49	$19.37 \leq 19.57 \leq 19.78$
2 <sup>nd</sup>	566,345	42.84	$3.585 \leq 3.593 \leq 3.600$
3 <sup>rd</sup>	701,259	37.00	$2.134 \leq 2.138 \leq 2.142$
4 <sup>th</sup>	141,552	44.56	$3.349 \leq 3.363 \leq 3.378$
5 <sup>th</sup>	1,487,886	43.41	$3.147 \leq 3.160 \leq 3.173$
6 <sup>th</sup>	6,112,305	41.84	$3.215 \leq 3.221 \leq 3.228$

The related Weibull parameters of the infection waves are documented in Table 2 including the 0.95 confidence belt for the shape parameter  $b$  and the number of cases in the period under consideration. At first, the differences in the number of cases between the infection waves become clear. For example, in the sixth wave, the number of cases was more than 250 times higher than in the first wave (in the same period of 56 days). The advantage of the use of Weibull distribution models is the normalization, so the analysis of spreading speed is possible despite these differences, cf. [12]. The findings regarding the spreading speed from Figure 3 are confirmed by the comparison of the shape parameters in Table 2. The shape parameter of the first wave is more than five times higher than the shape parameters in the other waves. The spreading speed in the second, fourth, fifth, and sixth waves are similar. Considering the confidence belts, there are minor, but significant differences between these waves. The third wave stands out with a lower spreading speed. This could be due to the predominant virus variant alpha in this infection wave.

Comparing the scale parameters of the different infection waves does not add any value to this analysis.

### 5.3 Lockdown impact

In Germany, with the status of March 2022, there were three delimitable lockdown measures. The corresponding periods under consideration with their predominant virus variants and characteristic measures can be found in the following table.

Table 3: Periods under consideration for three COVID-19 lockdown measures in Germany with key dates and characteristics.

Lockdown	Start date	End date	Predominant virus variant	Main valid measures
1 <sup>st</sup>	03/22/2020	05/16/2020	wild type	Shutdown of educational system, retail and gastronomy
2 <sup>nd</sup>	12/16/2020	09/02/2021	wild type/ alpha	Shutdown of educational system, retail and gastronomy, contact restrictions, masks
3 <sup>rd</sup>	04/23/2021	06/17/2021	alpha	Depending on the regional incidence: shutdown of educational system, retail and gastronomy, contact restrictions, curfews, masks

Note: The start dates of the different measures are the dates of entry into force. The end dates are defined by the period under consideration time span of 56 days of each pandemic phase in the analyses. In all lockdown hygiene measures and distance regulations were valid.

To evaluate the lockdown impact, Weibull distribution models are fitted for the three lockdown periods under consideration. For comparison, the first three COVID-19 waves are shown in the probability plot in Figure 4 together with the lockdown distribution models. These three waves are those that occurred shortly before the lockdown measures considered here were taken. In Table 3, the corresponding Weibull parameters are documented.

A clear difference can be noticed between the spreading behavior with lockdown measures and without lockdown measures. The gradient of the Weibull models and therefore the spreading speed was significantly reduced in the periods under consideration with lockdown measures. The strongest effect is noticeable at the first lockdown compared to the first wave. In this case, the spreading speed was reduced by a factor of  $\sim 14$ . The slowdown of the spreading speed in the second lockdown took place with a factor of  $\sim 2.5$ . During the third lockdown measure, the reduction of the spreading speed was with a factor of  $\sim 1.6$  the lowest. It has to be noted, that the spreading speed of the second and third waves was much lower than in the first wave. Therefore, it can be assumed, that the effect of the lockdown measures in the advanced pandemic course was not as relevant as in the first phase, cf. also [12].

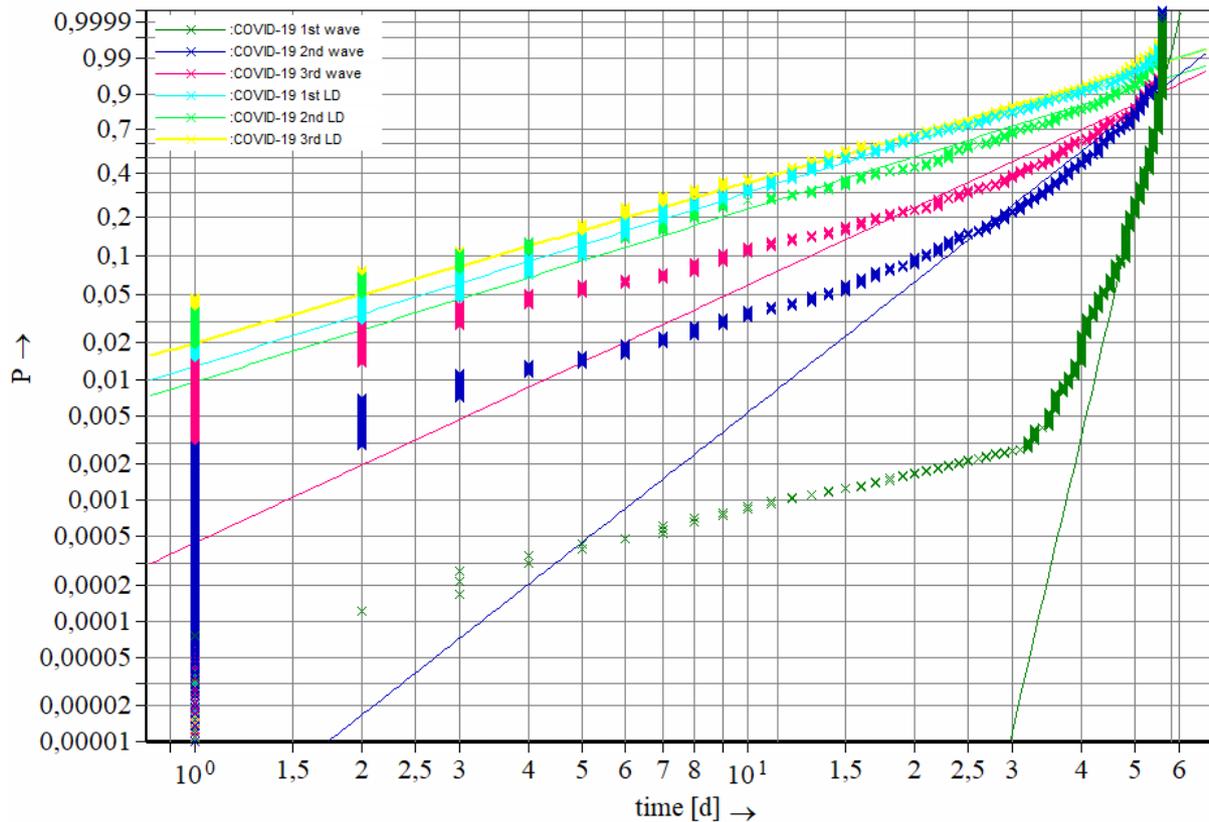


Figure 4: Weibull distribution models COVID-19 in Germany, comparison of different pandemic waves with lockdown (LD) impact, daily confirmed cases, time span 56 days.

Table 4: Weibull model parameters of different COVID-19 phases with lockdown impact in Germany (daily confirmed cases). Confidence level  $\gamma=0.95$ .

Phase	Cases	Scale T [d]	Shape b, confidence belt
1 <sup>st</sup> wave	22,255	53.49	$19.37 \leq 19.57 \leq 19.78$
2 <sup>nd</sup> wave	566,345	42.84	$3.585 \leq 3.593 \leq 3.600$
3 <sup>rd</sup> wave	701,259	37.00	$2.134 \leq 2.138 \leq 2.142$
1 <sup>st</sup> lockdown	153,539	20.49	$1.436 \leq 1.441 \leq 1.447$
2 <sup>nd</sup> lockdown	910,965	25.60	$1.430 \leq 1.433 \leq 1.435$
3 <sup>rd</sup> lockdown	473,061	18.82	$1.327 \leq 1.330 \leq 1.333$

### 5.4 Comparison with other infectious diseases

For an evaluation of the COVID-19 pandemic in a greater context, the spreading behavior is compared with other common notifiable diseases in Germany: Influenza, Norovirus, and Campylobacter enteritis, cf. [12]. Influenza is a seasonal (Winter half-year) respiratory infectious disease with symptoms like fever, cough, sore throat, or muscular pains. Infection occurs via droplets from person to person. The seasonal number of cases in Germany varies between 3,000 and 270,000 cases. Norovirus is a seasonal (winter months) gastro-intestinal disease with vomiting and diarrhea. The infection is fecal-oral or by droplets from person to person. The number of cases in Germany range between 60,000 and 100,000 cases per season. Campylobacter enteritis (CE) is also a gastrointestinal disease. It occurs seasonally in the warm season and shows symptoms like fever, diarrhea, and stomach ache. Unlike the Norovirus, this infectious disease is spread through food. The transmission from person to person is rather rare. The seasonal number of cases in Germany range between 50,000 and 70,000 cases. [14]

The comparison data set of the other infectious diseases [15] is given as weekly seasonal data. For a meaningful comparison, a five-year mean for each season week is estimated to avoid outliers. Therefore, the seasons from 2014/15 to 2018/19 are analyzed. The season 2019/20 is not considered for comparison

due to the interdependency of the concurrently valid COVID-19 measures. As the period under consideration following the previous analyses, an interval of eight weeks (56 days) is chosen. Thereby, an adequate amount of data points for the Weibull distribution fit is provided.

In Figure 5 the Weibull distribution models for the 5-year-means of Influenza, Norovirus, and CE are plotted as well as the models for the first and second COVID-19 wave and the first COVID-19 lockdown. The corresponding Weibull parameters are documented in Table 5. It gets clear that the unhindered spreading speed in the first COVID-19 wave is on a much higher level in comparison to other infectious diseases. This difference amounts to a factor of ~ 6 (Influenza) up to 9 (CE) in which the COVID-19 spreading speed is higher. The rate of spread was also significantly higher in the second wave, in which containment measures such as community masks were applied. As already shown in 12 [12], dismissing the COVID-19 spreading as the spreading of e.g. a “normal Influenza” is wrong and hazardous.

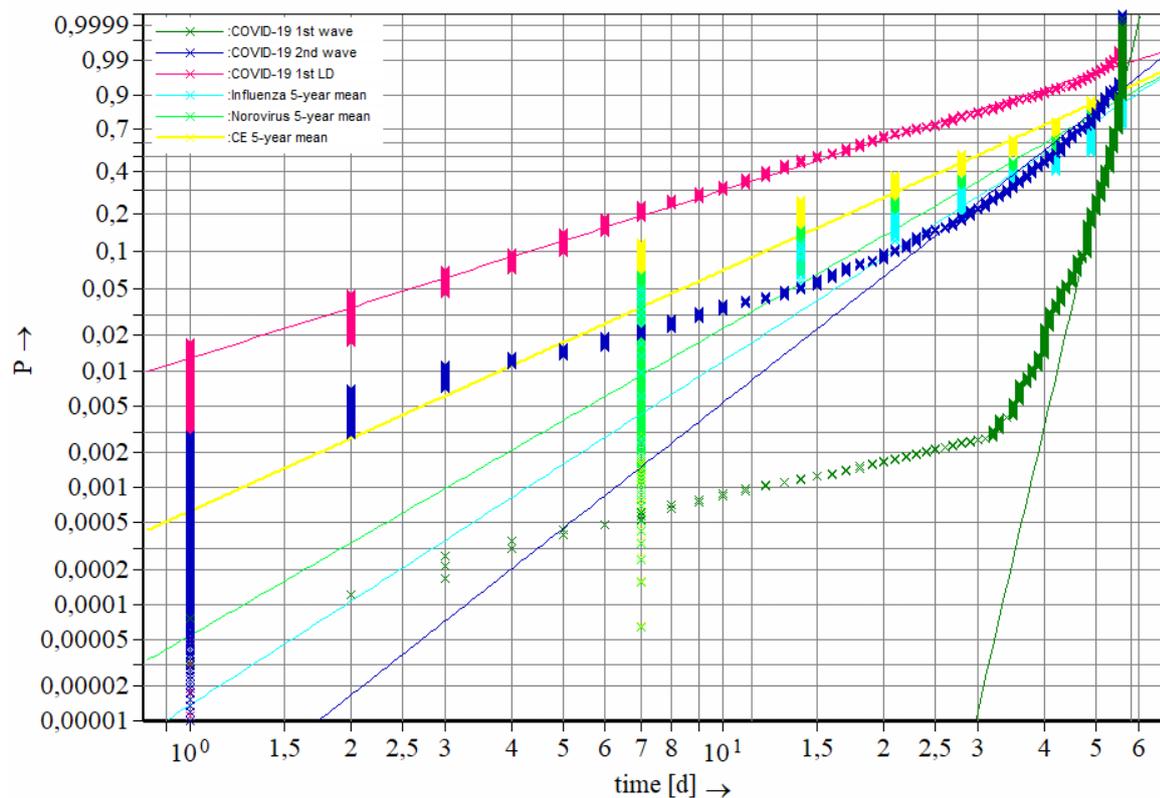


Figure 5: Weibull distribution models COVID-19 and other infectious diseases (5-year-mean 2014/15 to 2018/19) in season’s beginnings, daily confirmed cases, time span 56 days.

Table 5: Weibull model parameters COVID-19 and other infectious diseases in season’s beginnings (daily confirmed cases). Confidence level  $\gamma = 0.95$ .

Phase/disease	Cases	Scale T [d]	Shape b, confidence belt
1 <sup>st</sup> COVID-19 wave	22,255	53.49	$19.37 \leq 19.57 \leq 19.78$
2 <sup>nd</sup> COVID-19 wave	566,345	42.84	$3.585 \leq 3.593 \leq 3.600$
1 <sup>st</sup> lockdown COVID-19	153,539	20.49	$1.436 \leq 1.441 \leq 1.447$
Influenza	277	44.55	$2.676 \leq 2.950 \leq 3.237$
Norovirus	11,124	41.66	$2.596 \leq 2.625 \leq 2.675$
Campylobacter-Enteritis	10,660	35.45	$2.034 \leq 2.065 \leq 2.097$

With the lockdown impact in the first lockdown in March 2020, the spreading speed of COVID-19 was reduced under the level of the other infectious diseases. Only with strict lockdown measures like the shutdown of educational systems, retail, and gastronomy, the spreading speed of COVID-19 gets on a comparable level to the spreading speed of the analyzed infectious diseases Influenza, Norovirus, and CE. This outlines again the effectiveness of the lockdown measures to control the COVID-19 pandemic in the first wave.

## 6. CONCLUSION

In this paper, the method transfer from reliability engineering to epidemiology is the base for data analytics. Weibull distribution models were used for analyses of the occurrence of infection and spreading behavior of COVID-19. The central aspect is the analysis and the interpretation of the Weibull parameters shape parameter  $b$  (gradient), location Parameter  $T$ , and the dedicated confidence intervals. The base of operations regarding COVID-19 pandemic data are the data bases of JHU and RKI, focusing on Germany as a reference country. Furthermore, the statistical trend significance test Cox and Stuart is used for the detection of the infection waves.

The analyses show that a total of six main waves of infection can be detected in the first two years (Feb. 2020 - Feb 2022) of the COVID-19 pandemic in Germany. The characteristics of these six infection waves cannot be directly compared, as the waves are mainly characterized by different virus variants, number of cases, and different containment measures.

Nevertheless, the following results can be stated:

The spreading of the first wave - the increase in the number of infections - shows the highest speed compared to the other five waves: the gradient is five times faster. On the other hand, waves two to six have a similar speed of spread. In each case with respect to waves two to six, similar containment measures have been in place. At the same time, it can be noted that the lockdown to break the first wave has reduced the spreading speed the most (factor 14). The reduction in the following two cases was on a lower level (factor 2.5 and 1.6).

Comparing the spreading speed with known infectious diseases such as Influenza, Norovirus, and Campylobacter enteritis, the following summarizing statement can be noted: The unhindered spreading of the COVID-19 pandemic (first wave) occurs at a significantly higher speed than in comparison with Influenza (factor 6), Norovirus (factor 7), and Campylobacter enteritis (factor 9). It is noteworthy that only the strict measures of the first lockdown for the containment of the first wave resulted in a spreading speed of the COVID-19 wave that is below a common Influenza season. This shows the extraordinarily high spreading speed of the COVID-19 waves and the impact on the social life as well as the impact on the effectiveness of the business location Germany.

## References

- [1] S. Bracke and L. Grams, *Covid-19 Pandemic: Analyzing of Different Pandemic Control Strategies Using Saturation Models*, in: *Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021)*, B. Castanier, M. Cepin, D. Bigaud, and C. Berenguer, eds., ESREL 2021, Angers, France, 19-23 September 2021. Research Publishing Services, Singapore, 2021, pp. 2202–2207.
- [2] S. Bracke, A. Puls, and L. Grams, *COVID-19 pandemic data analytics: Data heterogeneity, spreading behavior, and lockdown impact*, in: *Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference*, P. Baraldi, F. Di Maio, and E. Zio, eds., ESREL 2020 PSAM 15, Venice, Italy, 1-5 November 2020. Research Publishing, Singapore, 2020, pp. 422–429.
- [3] S. Bracke, A. Puls, and M. Inoue, *COVID-19 pandemic: Analyzing of spreading behavior, the impact of restrictions and prevention measures in Germany and Japan*, in: *Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021)*, B. Castanier, M. Cepin, D. Bigaud, and C. Berenguer, eds., ESREL 2021, Angers, France, 19-23 September 2021. Research Publishing Services, Singapore, 2021, pp. 969–976.
- [4] D.R. Cox and A. Stuart, *Some Quick Sign Tests for Trend in Location and Dispersion*, *Biometrika* 42 (1955), pp. 80–95.

- [5] ECDC, *Data on SARS-CoV-2 variants in the EU/EEA*. Available at <https://web.archive.org/web/20220306162025/https://www.ecdc.europa.eu/en/publications-data/data-virus-variants-covid-19-eueea>.
- [6] R.A. Fisher, *On an Absolute Criterion for Fitting Frequency Curves*, *Messenger of Mathematics* (1912), pp. 155–160.
- [7] L. Gattinoni, D. Chiumello, P. Caironi, M. Busana, F. Romitti, L. Brazzi, and L. Camporota, *COVID-19 Pneumonia: Different Respiratory Treatments for Different Phenotypes?*, *Intensive care medicine* 46 (2020), pp. 1099–1102.
- [8] GISAID, *GISAID EpiCoV database*. Available at <https://www.gisaid.org/>.
- [9] JHU, *COVID-19 Dashboard*. Available at <https://coronavirus.jhu.edu/map.html>.
- [10] W.O. Kermack and A.G. McKendrick, *A contribution to the mathematical theory of epidemics*, *Proc. R. Soc. Lond. A* 115 (1927), pp. 700–721.
- [11] A. Puls and S. Bracke, *COVID-19 Pandemic Risk Analytics: Data Mining with Reliability Engineering Methods for Analyzing Spreading Behavior and Comparison with Infectious Diseases*, in: *Reliability Engineering and Computational Intelligence*, C. van Gulijk and E. Zaitseva, eds. Springer International Publishing, Cham, 2021, pp. 293–307.
- [12] A. Puls and S. Bracke, *Reliability Methods for Analyzing Covid-19 Pandemic Spreading Behavior, Lockdown Impact and Infectiousness*, in: *Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021)*, B. Castanier, M. Cepin, D. Bigaud, and C. Berenguer, eds., ESREL 2021, Angers, France, 19-23 September 2021. Research Publishing Services, Singapore, 2021, pp. 961–968.
- [13] H. RINNE, *The Weibull Distribution: A Handbook*. CHAPMAN & HALL CRC, [S.l.], 2020.
- [14] RKI, *Infektionsepidemiologisches Jahrbuch meldepflichtiger Krankheiten für 2019: Datenstand: 1. März 2020*, 2019.
- [15] RKI, *SurvStat@RKI 2.0: Web-based query on data reported under the German 'Protection against Infection Act'*. Available at <https://survstat.rki.de/Default.aspx>.
- [16] M.M. Sajadi, P. Habibzadeh, A. Vintzileos, S. Shokouhi, F. Miralles-Wilhelm, and A. Amoroso, *Temperature, Humidity, and Latitude Analysis to Estimate Potential Spread and Seasonality of Coronavirus Disease 2019 (COVID-19)*, *JAMA network open* 3 (2020).
- [17] W. Weibull, *A Statistical Distribution Function of Wide Applicability*, *Journal of Applied Mechanics* (1951), pp. 293–297.