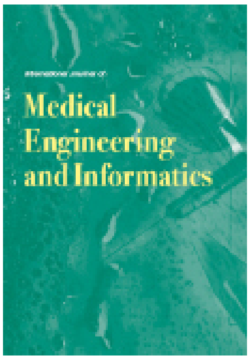


International Journal of Medical Engineering and Informatics

ISSN online: 1755-0661 - ISSN print: 1755-0653
https://www.inderscience.com/ijmei

Analysis and trends of COVID-19 in Italy

Cinzia Muriana, Giovan Battista Vizzini

DOI: 10.1504/IJMEI.2022.10049913

Article History:

Received:	15 February 2022
Accepted:	13 July 2022
Published online:	12 December 2024

Analysis and trends of COVID-19 in Italy

Cinzia Muriana* and Giovan Battista Vizzini

University of Pittsburgh Medical Center Italy SRL,
Via Discesa dei Giudici 4, 90133 Palermo, Italy
Email: murianac@upmc.it
Email: vizzinig@upmc.it
*Corresponding author

Abstract: SARS-CoV-2 is impacting the public health-system worldwide and requires policies to address the demand for additional capacity. Monitoring its spread allows the identification of alarm signals useful for scaling up resources and reacting to the pandemic. In Italy, starting with the identification of the first patient, the Protezione Civile has published a range of indicators as open data, which has supported the country's government in discovering trends and in setting-up targeted measures for preventing the spread of the virus and controlling the speed of transmission. This paper analyses these indicators from February 2020 to June 2021 and provides insights for healthcare managers.

Keywords: SARS-CoV-2 outbreak; SARS-CoV-2 predictors; COVID-19 response; outbreak monitoring; Italy.

Reference to this paper should be made as follows: Muriana, C. and Vizzini, G.B. (2025) 'Analysis and trends of COVID-19 in Italy', *Int. J. Medical Engineering and Informatics*, Vol. 17, No. 1, pp.13–29.

Biographical notes: Cinzia Muriana was graded as PhD in the field of Production Engineering at the University of Palermo, where she also covered a position of Post Doc. Currently, she covers the position of Project Manager at UPMC Italy SRL, where she is involved in the management of research projects, granted by European, national or regional public authorities. Her main research fields relate to project management and healthcare assessment, with regard to risk management in healthcare, decision support systems, big data, and information communication technologies for healthcare organisations. She is also active in the field of logistics with particular regard to the optimisation of supply chain management and food recovery/waste management.

Giovan Battista Vizzini is specialised in transplantation medicine, hepatology and gastroenterology. He is currently the Chief Operating Officer of UPMC Italy and Medical Director of UPMC-SMIH-Rome. He is an Associate Professor of Medicine at the University of Pittsburgh School of Medicine. He has led the transplantation hepatology clinical group since the start, in 1999, of the liver transplantation program managed by UPMC at ISMETT IRCSS in Palermo. He is the author of more than 100 publications. His main research fields are: liver transplantation, diagnosis and treatment of hepatocellular carcinoma, of viral hepatitis B and C, treatment of portal hypertension.

1 Introduction

The SARS-CoV-2 pandemic – also known as the COVID-19 outbreak – has spread all over the world since being first identified in December 2019. In Italy, the virus was isolated in February 2020 in Codogno (Lombardy, Northern Italy). Healthcare organisations immediately started recording a set of performance indicators related to SARS-CoV-2, with the aim of monitoring the pandemic trend and letting the regional and central governments take targeted decisions for the management of the outbreak. Starting in February 2020, these indicators were published as open data daily by the 'Protezione Civile' (PC) (http://www.protezionecivile.it/). Likewise, online newspapers have been publishing data related to the SARS-CoV-2 pandemic (e.g., 'Ilsole24ore', https://lab24.ilsole24ore.com/coronavirus/).

The main issue that the national health system faces in Italy is that of providing the right assistance based on the severity of symptoms. We discriminate among people with severe symptoms, moderate symptoms (paucisymptomatic) and those who are asymptomatic. The timeline in Italy is as follows: we experienced the first epidemic wave from February 2020 to June 2020; a second wave hit the country from September 2020 to February 2021; and a third wave was registered from February 2021 to June 2021. At the time of writing (August 31, 2021), the third epidemic wave had ended. As regards the first wave, the primary concern of the central government was that of lowering the peak number of inpatients and people in emergency units as much as possible and increasing the number of resources (beds and caregivers) to assist as many people as possible. Thus, a total lockdown was implemented (March 9, 2020–May 3, 2020). When the first epidemic wave ended (June 2020), the central government massively promoted screenings, even providing domiciliary assistance, to identify asymptomatic people and isolate them in order to reduce the possibility of infection, all the while working towards the validation of the SARS-CoV-2 vaccine. Starting from this time, the government approach has been to promote targeted restrictions for the different regions of Italy, where the occupancy of ICUs, the hospitalisation units and the R_t (a measure of the spread of infection) must be monitored weekly and compared with fixed thresholds. Based on these criteria, each region is labelled 'white', 'yellow', 'orange', or 'red', with each colour representing an increasing level of risk of infection and a corresponding increase in the level of restrictions.

At the time of writing (August 31, 2021), 'Ilsole24ore' reported that 25.2% of deaths were in people aged 70 or over, 40.3% were over 80, and 19.4% were over 90. Based on the statistics reported in 'Impatto dell'epidemia covid-19 sulla mortalità: cause di morte nei deceduti positivi a SARS-CoV-2' 2020, an ISTAT technical report, SARS-CoV-2 was the principal cause of death in 89% of people testing positive for SARS-CoV-2 between February 2020 and January 2021. The percentage deaths where SARS-CoV-2 was the direct cause varies according to age, reaching a maximum value of 92% in the 60–69 age class and a minimum value of 82% in people under 50.

It is worth highlighting that a pandemic is a non-stationary process and the time series of the related indicators might not be characterised by known trends, nor be easily fitted using known functions or distributions. This makes it very difficult for a healthcare system to adapt the production capacity in the short term. In fact, when the volume of patients to be assisted suddenly increases, caregivers and healthcare structures become the bottleneck, and managers must be ready to respond to the increasing demand for resources.

Knowing this, the goal of the paper is to analyse the data provided by the PC on infected people, inpatients, people isolated at home, and deaths which were registered during the three pandemic waves that hit Italy from February 2020 to June 2021, and to identify useful graphs and information that can result in insights for healthcare managers.

2 Review of the literature and goal of the paper

2.1 Outbreak modelling

Generally, when speaking of pandemics, the interest of the researchers is focused on modelling the evolution of the pandemic to optimise the indicators that are mainly responsible for the spread of the virus from the standpoint of infectious management. The approaches usually rely on differential equations, Markovian chains, and/or mathematic optimisation (for reference, see Yan, 2008).

The model mainly used is 'susceptible, infectious, recovered' developed in the early 20th century [SIR, see Bjørnstad et al. (2020) for a review]. This model can be continuous or discrete, and deterministic or stochastic. Evolutions of the model include births and deaths, naturally vaccinated people, and the reproductive number, as described in Hethcote (2000), Tuckwell and Williams (2007) and Getz et al. (2018).

2.2 Management and impact of SARS-CoV-2

Observing the SARS-CoV-2 outbreak, researchers have explored the issue from all standpoints, such as epidemiologic, psychosocial, economic, logistic, and poverty-related. Moreover, great attention has been paid to the health policies put into practice for the management of the pandemic. Unruh et al. (2022) highlighted a number of factors that are central to an effective pandemic response, such as appropriate containment and mitigation measures; strong and consistent leadership; evidence-based, transparent decision-making; coordinated testing, tracing and isolation systems; universal coverage; and a sufficient health and social care workforce. Winkelmann et al. (2022) analysed the strategies taken by 45 countries in Europe and found that all of them designated COVID-19 units and expanded hospital and ICU capacities. They concluded that coordination mechanisms informed by real-time monitoring as well as close cooperation between countries are essential to building resilient responses to SARS-CoV-2. Pelagatti and Maranzano (2021) examined the restrictions introduced by the Italian government, based on an increasing level of risk, indicated as yellow, orange, and red policies. They found that 'yellow' leads to a constant number of hospitalisations (zero growth rate), 'red' is capable of halving the number of accesses in about one month, while 'orange' seems to be only slightly more effective than the yellow policy. Bosa et al. (2021) investigated the different responses to SARS-CoV-2 reflecting on seven management factors: monitoring, learning, decision-making, coordinating, communicating, leading, and recovering capacity, and concluded that the most relevant are leadership and recovery capacity. Kumpunen et al. (2022) examined primary healthcare (PHC) delivery models in Europe during the pandemic and identified three prevalent models:

1 multi-disciplinary primary care teams

2 PHC providers defining and identifying vulnerable populations for medical and social outreach

3 PHC providers employing remote digital solutions.

Lee and Morling (2020) identified the main lessons learned as: 'rapid response', 'measures for containing the virus spread', 'transparency of information', 'community engagement', 'focus on the social gradient in examining the distribution of the outbreak', 'public health threats and investments', and 'global health security (socio-economic impact of the outbreak)'.

3 Technical approach

The technical approach is that of time series analysis provided as open data by the PC in Italy (http://www.protezionecivile.it/). The analysis of the time series will allow us:

- to analyse data related to infected people, inpatients, people isolated at home, deaths, etc., and promptly identify alarm signals that can promote timely decision-making activities under uncertain outbreak-related scenarios
- to identify the most significant indicators involved in the SARS-CoV-2 outbreak and to provide effective and easy-to-implement visual representations of such
- to discover possible relationships among the time series
- to understand how the pandemic is progressing
- to abstract from specific cases and derive new insights for healthcare managers for future experiences.

In the rest of the document, we will indicate the day t^{th} as t. Moreover, our convention for the time windows for the three pandemic waves are:

- time horizon (TH): February 24, 2020 to June 29, 2021: [TH duration= 492 days]
- first pandemic wave (FPW): February 24, 2020 to June 12, 2020: [FPW duration= 110 days]
- second pandemic wave (SPW): August 20, 2020 to February 16, 2021: [SPW duration = 181 days]
- third pandemic wave (TPW): February 17, 2021 to June 29, 2021: [TPW duration = 133 days].

3.1 Analysis of the time series

3.1.1 Comparison of the curves 'percentage of newly infected at day t' ('i_{perc}') vs. 'number of deaths at day t' ('d_t')

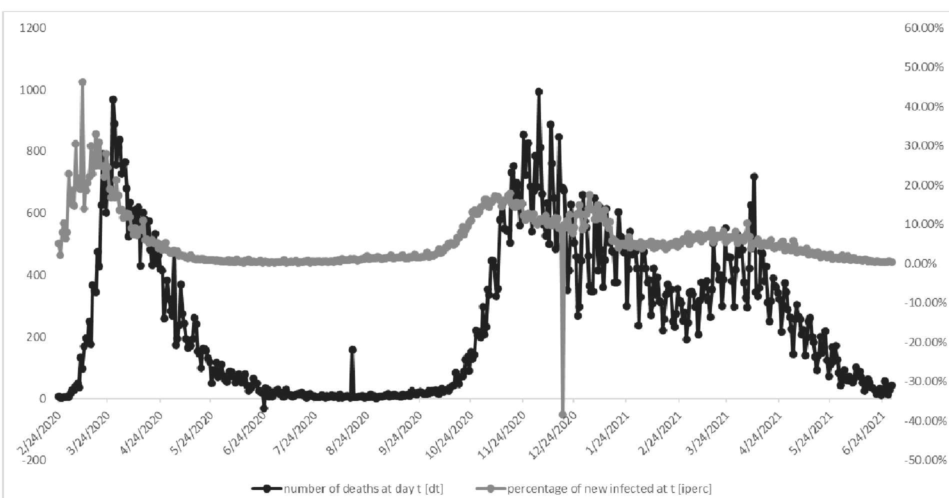
The comparison of the curves 'i_{perc}' and 'd_t' (see Figure 1) shows that the time window between the peaks of the two indicators was: FPW -> 18 days, SPW -> 17 days, TPW -> 4 days.

In all pandemic waves, the peak of i_{perc} preceded that of d_t. We found a weak correlation between the two indicators for the TH ($R = 0.5060$, $R^2 = 0.2560$), while regression analysis showed that the dependence of d_t on i_{perc} is significant. The monthly average i_{perc} for the three waves was 2.53% for the FPW, 1.27% for the SPW, and 0.92% for the TPW.

Insights

The lack of a strong correlation between i_{perc} and d_t suggests positive feedback on the overall impact of the virus on the population, in that it confirms that the infection itself is not directly responsible for deaths. The average values highlight that the spread of the virus decreased moving from the FPW to the TPW, and this is the effect of multiple concurrent factors, such as restrictions, distancing, vaccination and, perhaps, the reduced virulence of the virus itself.

Figure 1 Comparison of the curves 'i_{perc}' and 'd_t' ('i_{perc}' values should be read on the right vertical axis)



3.1.2 Comparison of the curves 'percentage of newly infected at day t' ('i_{perc}') vs. 'number of patients in ICU to day t (cumulative)' ('ICU_t')

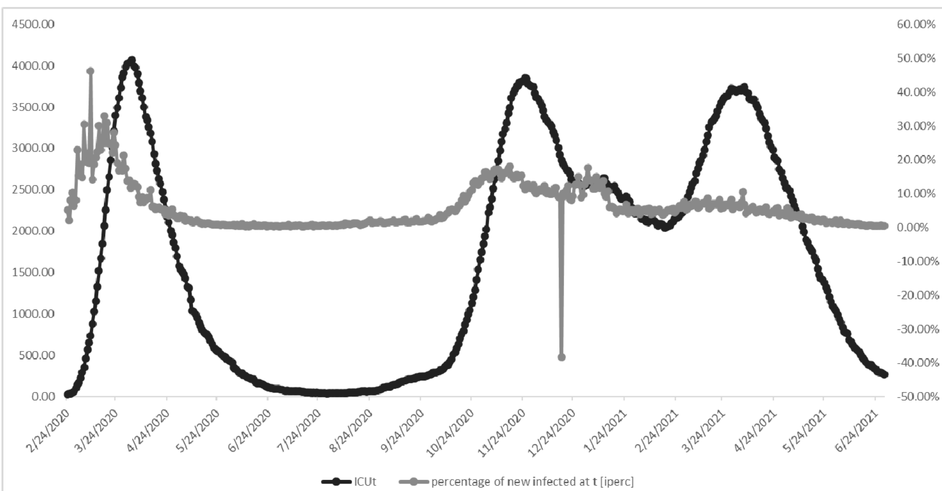
Comparing the curve 'i_{perc}' with the curve 'ICU_t' (see Figure 2), we found that the time window between the two peaks was: FPW -> 25 days, SPW -> 9 days, TPW -> 1 day.

In all pandemic waves, the peak of i_{perc} preceded that of ICU_t. We found a weak correlation between the two indicators for the TH (R = 0.4868, R_2 = 0.2370), while linear regression analysis showed that the dependence of ICU_t on i_{perc} is significant.

Insights

The increase in i_{perc} should be monitored as it indicates alarm conditions for the subsequent increase in patients in ICU. It is worth highlighting that when the ICU reaches its peak, the i_{perc} curve is already descending, meaning that the pandemic wave is already lowering. This finding is verified for all three pandemic waves. This can probably be interpreted by saying that the ICU occupancy is due to both new entries and previously hospitalised people who remain in ICU for a long time due to the persistence of serious conditions.

Figure 2 Comparison of the curves 'i_{perc}' and 'ICU_t' ('i_{perc}' values should be read on the right vertical axis)



3.1.3 Comparison of the curves 'number of patients in ICU to day t (cumulative)' ('ICU_t') vs. 'number of deaths at day t' ('d_t')

Comparing the peak 'ICU_t' with the peak of 'd_t' (see Figure 3), we found that the time window between the two peaks was: FPW -> -7 days, SPW -> 8 days, TPW -> 3 days.

Comparing the peak of the 'daily increment/decrement of the number of patients in ICU' ('icu_t') with that of 'd_t', we found: FPW -> 8 days, SPW -> 30 days, TPW -> 26 days. Except for the FPW, the peak ICU_t always preceded that of d_t. We found a high correlation between the two curves for the TH (R = 0.9076, R^2 = 0.8238) and linear regression showed that ICU_t is a good predictor for d_t, (see the scatterplot in Figure 4). Observing the patients hospitalised in ICU and the number of deaths, we noticed that the monthly average number of patients hospitalised in ICU, $\overline{ICU_j}$, was 1,119.63 for the FPW, 641.333 for the SPW and 850.682 for the TPW, while the monthly average number of deaths $\overline{d_j}$, was 9,419.17 for the FPW, 9,793.17 for the SPW and 7,584.32 for the

TPW. Calculating the ratio $\frac{\overline{d_j}}{\overline{ICU_J}}$, we found that it was 8.412 during the FPW, 15.27 during the SPW and 8.915 during the TPW.

Figure 3 Comparison of curves 'd_t' and 'ICU_t' (d_t values should be read on the right vertical axis and ICU_t on the left vertical axis)

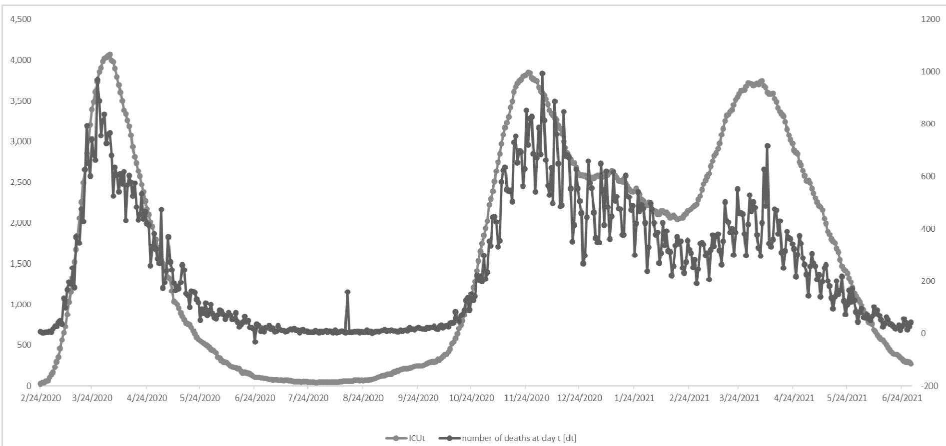
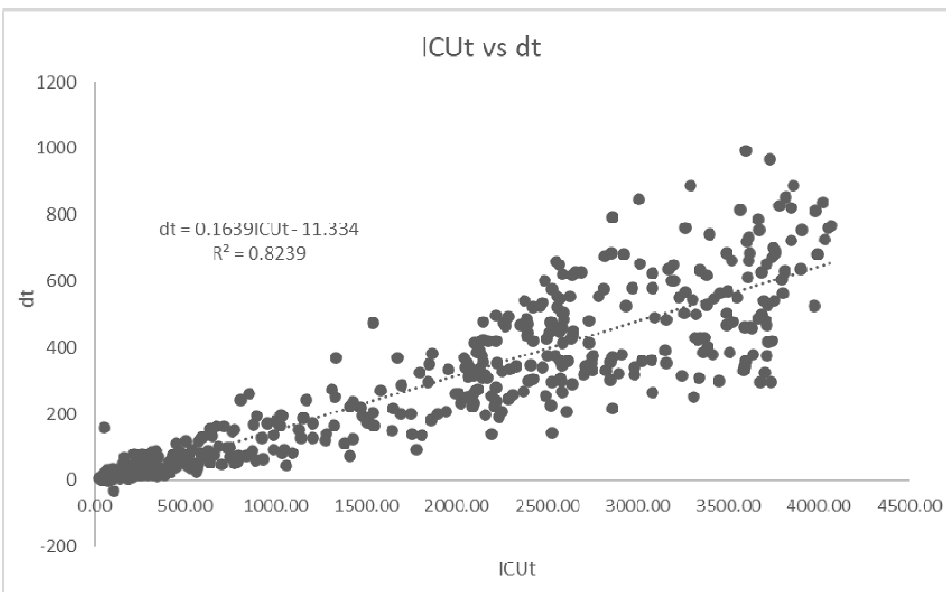


Figure 4 Scatter plot of ICU_t vs. d_t



Insight

Similar to what is seen in Subsection 3.1.2, during the FPW when ICU_t reaches its peak, the d_t curve is already descending. Once again, this can be attributed to the long hospitalisation of patients in a serious condition. However, during the SPW and the TPW, the two curves have superimposable trends. The ratio $\frac{\overline{d_j}}{\overline{ICU_J}}$ highlights that the SPW was the most aggressive in terms of deaths, followed by the TPW.

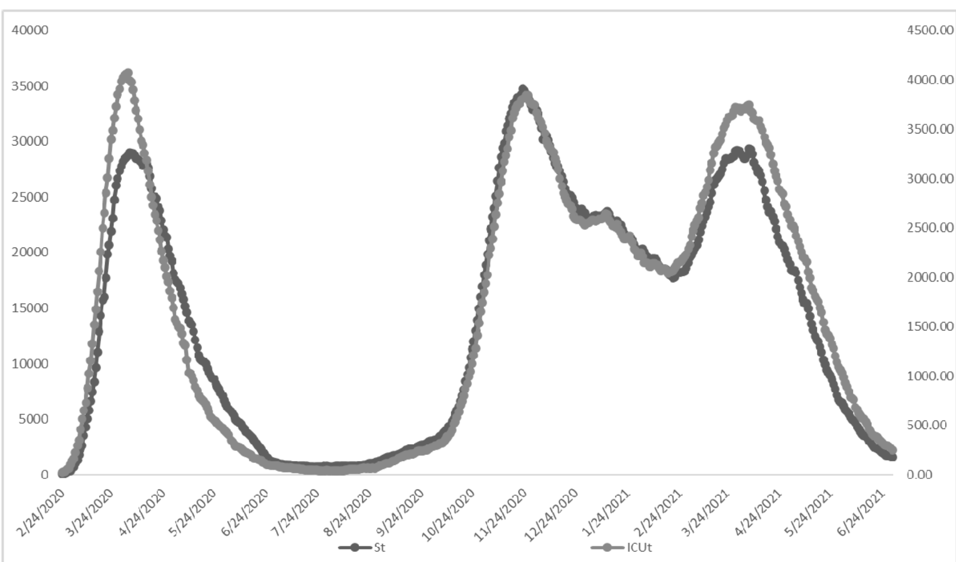
3.1.4 *Comparison of the curves 'number of patients in ICU to day t (cumulative)' ('ICU_t') vs. 'inpatients (symptomatic) excluding patients in ICU to day t (cumulative)' ('S_t')*

The comparison of the curves 'ICU_t' and 'St' (see Figure 5) shows that the time window between the two peaks was: FPW -> –1 day, SPW -> 2 days, TPW -> 0 days.

The correlation analysis showed that the two indicators are strictly related for the TH ($R = 0.9780$, $R^2 = 0.9565$, see the scatterplot in Figure 6). St is a good predictor of ICU_t, as shown by linear regression analysis.

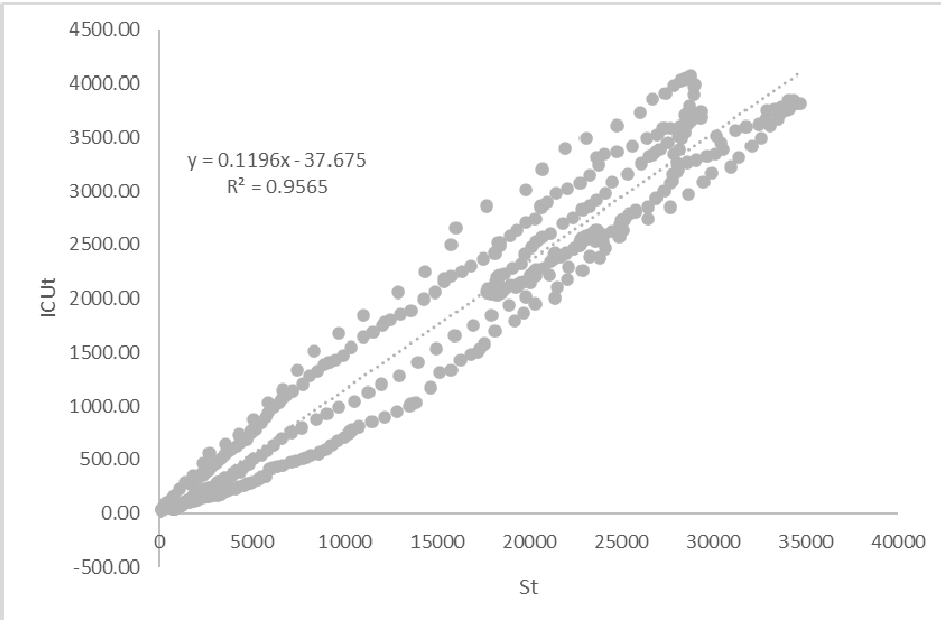
Observing the peaks of the two curves, we noticed that: the number of patients in ICU decreased from the FPW to the TPW, and that the ratio between S_t and ICU_t was 7.13 (29,010/4,068) for the FPW, 9.01 for the SPW (34,697/3,848) and 7.83 for the TPW (29,337/3,743).

Figure 5 Comparison of the curves 'S_t' and 'ICU_t' (ICU_t values should be read on the right vertical axis)



The peak S_t was 94.60% during the FPW, 94.41% during the SPW, and 89.94% during the TPW. We also considered the indicator 'H_{perc}', the 'percentage of positive people isolated at home (cumulative)', which is the ratio between the 'number of positive people isolated at home (cumulative)' and the 'number of positive people (cumulative)' ('P_t'). The average value of this indicator for each pandemic wave was 67.73% for the FPW, 94.70% for the SPW, and 95.34% for the TPW. Finally, analysing the ratio between the average monthly values of 'ICU_t' and that of the 'total number of inpatients (symptomatic + ICU) to day t (cumulative)' ('IN_t') for the three waves, we found 12.33% for the FPW, 9.99% for the SPW, and 11.31% for the TPW.

Figure 6 Scatter plot of 'ICU_t' vs. 'S_t'



Insights

The analysis of the peaks of the two curves suggests that the FPW was the most aggressive as it was mainly characterised by a higher number of patients in ICU. The peak of S_t, which does not include ICU_t, suggests that most of the hospitalised patients had mild symptoms. This information is also supported by the average values of 'H_{perc}'. Finally, the ratio between the average monthly values of 'ICU_t' and 'IN_t' suggests that during the SPW fewer people were hospitalised in ICU, as IN_t includes both S_t and ICU_t.

3.1.5 *Analysis of the 'daily increment/decrement of the number of patients in ICU' ('icu_t') and 'number of patients in ICU to day t (cumulative)' ('ICU_t')*

The analysis of people in ICU (both 'ICU_t' and 'icu_t', see Figure 7) aims to identify:

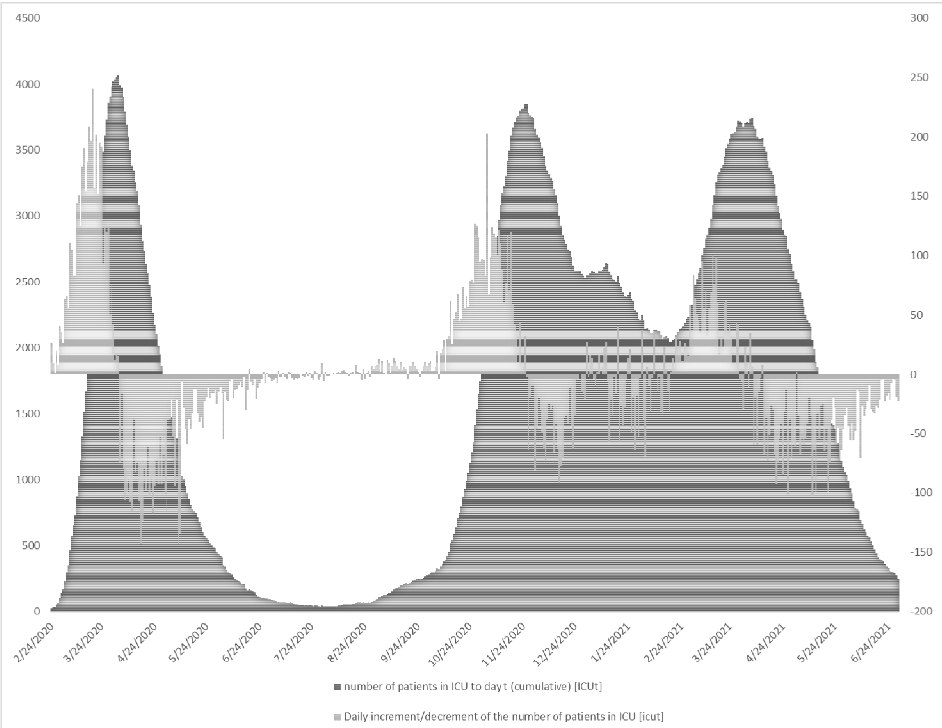
a the time window during which the number of new patients in ICU increases day by day (increasing rate of hospitalisation in ICU) and that during which it decreases (decreasing rate of hospitalisation in ICU)

b the time instant at which the increment/decrement of patients in ICU reaches its peak

c the number of patients in ICU when the peak is reached.

For this purpose, the histograms of 'ICU_t' and 'icu_t' of the FPW, SPW and TPW in Italy were considered and these are reported in Figure 7.

Figure 7 Analysis of the of 'ICU_t' and 'icu_t' histograms ('icu_t' values should be read on the right vertical axis)



As seen in Figure 8, from the first day of observation to the 25th day of observation the rate of patients in ICU increased, meaning that the number of patients entering the ICU exceeded that of patients leaving the ICU (number of patients entering the ICU minus number of patients leaving the ICU > 0, positive balance). In that period of time, the average daily increment was +21.74.

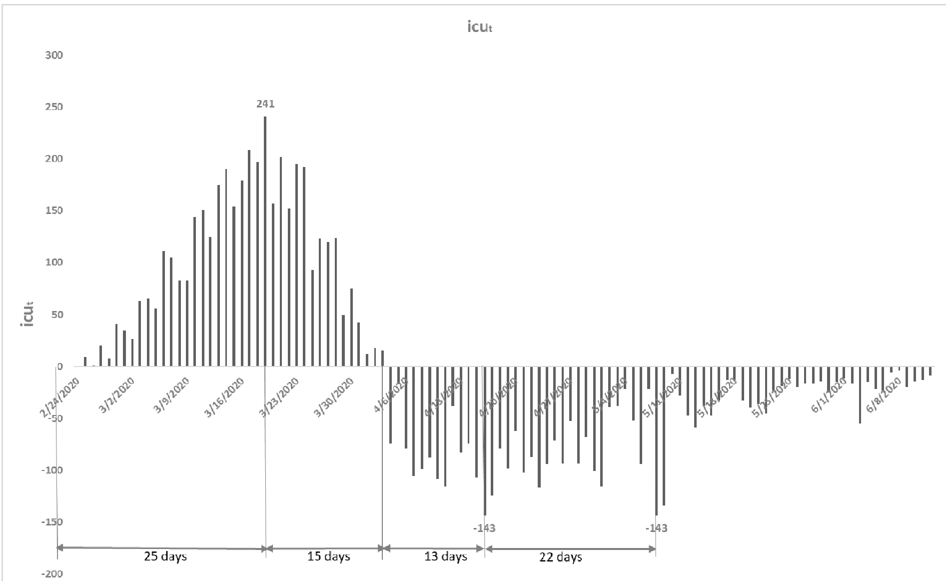
The increment of patients in ICU reached its peak on the 25th day of observation when it was +241 patients. Using incremental values instead of absolutes allows managers to identify variations in the ICU_t curve slope and predict in advance the increase (or decrease) in ICU occupancy. So, for example, the peak of the increment +241 patients represents an alarm condition of the increase in new patients in ICU starting from this date. It anticipates the peak ICU_t after 15 days; this allows managers to widen production capacity (beds/health-care operators).

From the 26th day of observation to the 40th day of observation the rate of patients entering the ICU decreased, meaning that the number of patients entering the ICU was lower than that of patients leaving the ICU (number of patients entering the ICU minus number of patients leaving the ICU < 0, negative balance). In that period of time, the average daily decrement was 3.33%. The decrement of patients in ICU reached a minimum on the 40th day of observation, when it was +15 patients.

In total, 40 days passed from the first day of detection to when the inversion of the rate was registered.

From the 41st day of observation to the 110th day of observation the daily average decrement was –4.01. During this period, the decrement of patients in ICU increased continuously, reaching its peaks on the 53rd day of observation and the 75th day of observation, when it was –143 patients on both dates.

Figure 8 Zoom of the 'icu_t' histogram for the FPW



Finally, the number of patients in ICU dropped to zero around the 110th day of observation, when the emergency in the ICU ended. Similarly, with regard to the increment, the negative peak indicates the speed of emptying of the ICU.

Similar considerations can be made for the SPW and the TPW.

Summarising

The peak number of patients in ICU was registered 40 days after the first time the data were gathered and was 4,068 patients. During this time window, the increment in patients in ICU was on average +21.74% per day. From the 41st day of observation to the 110th day of observation, the decrement of patients in ICU was -4.01% on average per day.

Insights

During the FPW, the filling of the ICU was very speedy, while emptying was less rapid; in fact, it was three times lower than the rate of filling. When the peak 'icu_t' is reached, managers know in advance that the peak 'ICU_t' is going to be reached. They can provide financial resources to boost surge capacity in the ICU and easily track the peak. When the increment is close to zero (horizontal axis), managers know that the peak has been reached and starting from the next day the number of patients in ICU will start to decrease (negative values of increment). Using histograms that report the incremental values is very useful as it allows us to evidence some critical time instants. For example, using the histograms of 'icu_t' and 'ICU_t' allows us to identify:

1 the day at which the maximum increment of patients in ICU (peak of the ‘icu_t’ curve) is registered

2 the day at which the peak is reached in ICU (day at which ‘ICU_t’ is maximum and ‘icu_t’ is zero or the increment is null)

3 the day at which the increment of new patients in ICU starts to decrease (day at which ‘icu_t’ values are negative)

4 the day at which we do not register new patients in ICU, i.e., when the values of icu_t are close to the horizontal axis.

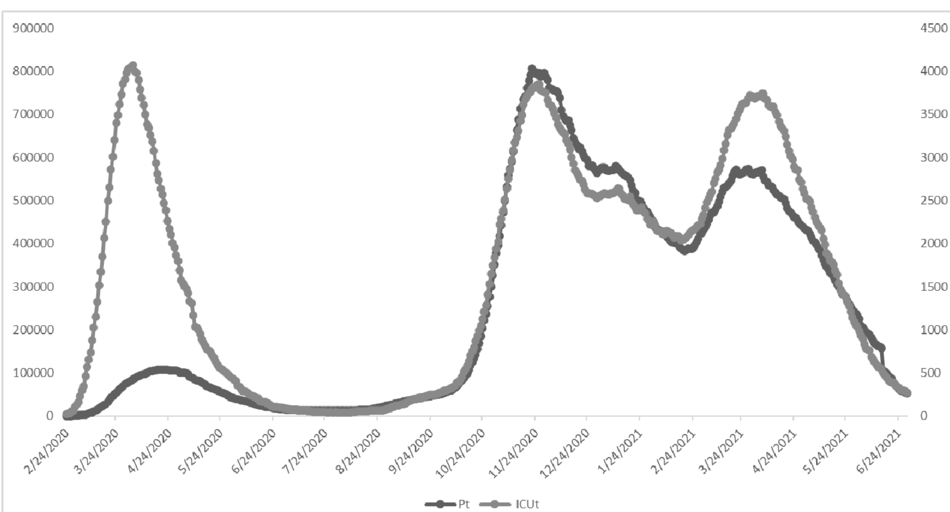
This simple representation is an effective dashboard for monitoring other indicators like ‘IN_t’ or ‘S_t’.

3.1.6 Comparison between the ‘number of people positive to SARS-CoV-2 to day t (cumulative)’ (‘P_t’) and the ‘number of patients in ICU to day t (cumulative)’ (‘ICU_t’)

The comparison of the two time series ‘P_t’ and ‘ICU_t’ during the TH (see Figure 9) shows that the time window between the two peaks was: FPW -> –16 days, SPW -> 3 days, TPW -> 9 days.

Except for the FPW, the peak of P_t preceded that of ICU_t. We found a good correlation between the two indicators for the TH ($R = 0.7929$, $R^2 = 0.6288$). Regression analysis showed that the dependence of ICU_t on P_t is significant.

Figure 9 Comparison between ‘P_t’ and ‘ICU_t’ and (‘ICU_t’ values should be read on the right vertical axis)



Insights

P_t is a good predictor for ICU_t and, thus, its increase should be monitored as it indicates alarm conditions for the subsequent increase in the number of patients in ICU.

The most significant results of the questions addressed in the previous sections are summarised in Table 1, which can be useful for future experiences, possibly for implementing automatic and real-time calculations to provide healthcare managers with support systems (like dashboards).

Table 1 Summary of major insights

Subsection	*Indicators analysed*		*Major insight*
3.1.1	i_{perc}	d_t	i_{perc} is a reliable predictor for d_t
3.1.2	i_{perc}	ICU_t	i_{perc} is a reliable predictor for ICU_t
3.1.3	ICU_t	d_t	ICU_t is a good predictor for d_t
3.1.4	S_t	ICU_t	S_t is a good predictor for the increase in ICU_t
3.1.5	icu_t		icu_t histogram is a good representation for monitoring the level of ICU saturation, for predicting the achievement of the peak of hospitalised patients in ICU, the variation of the filling rate and the ending of the emergency in ICU units
3.1.6	P_t	ICU_t	P_t is a reliable predictor for ICU_t

3.2 Concise view – comparison between the three pandemic waves

The following tables report the results of a one-way ANOVA analysis for certain indicators. The one-way ANOVA showed that the differences between the three waves in terms of average values were statistically significant for the indicators ICU_t, 'Number of people positive to SARS-CoV-2 identified at day t' (p_t) P_t, d_t and i_{perc} whereas the one-way ANOVA was not significant for the indicators S_t, or IN_t [see Tables 2(a)–2(g)].

Table 2(a) S_t

Groups	*Number*		*Sum*	*Average*		*Variance*
FPW	110		1.58E+06	1.44E+04		9.05E+07
SPW	181		3.06E+06	1.69E+04		1.28E+08
TPW	133		2.23E+06	1.67E+04		8.39E+07
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	5.01E+08	2.00	2.50E+08	2.40	0.09	3.02
Within groups	4.40E+10	421.00	1.04E+08			
Total	4.45E+10	423.00				

Table 2(b) ICU_t

Groups	*Number*		*Sum*	*Average*		*Variance*
FPW	110		1.82E+05	1.66E+03		1.74E+06
SPW	181		3.32E+05	1.84E+03		1.62E+06
TPW	133		2.93E+05	2.20E+03		1.27E+06
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	1.93E+07	2.00	9.65E+06	6.27	0.00	3.02
Within groups	6.48E+08	421.00	1.54E+06			
Total	6.67E+08	423.00				

Table 2(c) IN_t

Groups	*Number*		*Sum*	*Average*	*Variance*	
FPW	110		1.76E+06	1.60E+04	1.16E+08	
SPW	181		3.39E+06	1.88E+04	1.58E+08	
TPW	133		2.52E+06	1.89E+04	1.06E+08	
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	6.45E+08	2	3.22E+08	2.46	0.09	3.02
Within groups	5.51E+10	421	1.31E+08			
Total	5.57E+10	423				

Table 2(d) p_t

Groups	*Number*		*Sum*	*Average*	*Variance*	
FPW	110		2.36E+05	2.15E+03	3.30E+06	
SPW	181		2.49E+06	1.37E+04	1.11E+08	
TPW	133		1.51E+06	1.14E+04	6.30E+07	
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	9.56E+09	2	4.78E+09	70.40	0.00	3.02
Within groups	2.86E+10	421	6.79E+07			
Total	3.82E+10	423				

Table 2(e) P_t

Groups	*Number*		*Sum*	*Average*	*Variance*	
FPW	110		6.63E+06	6.03E+04	1.30E+09	
SPW	181		6.94E+07	3.83E+05	7.44E+10	
TPW	133		5.00E+07	3.76E+05	2.54E+10	
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	8.35E+12	2	4.17E+12	104.06	0.00	3.02
Within groups	1.69E+13	421	4.01E+10			
Total	2.52E+13	423				

Table 2(f) d_t

Groups	*Number*		*Sum*	*Average*	*Variance*	
FPW	110		3.42E+04	3.11E+02	6.53E+04	
SPW	181		5.88E+04	3.25E+02	7.11E+04	
TPW	133		3.34E+04	2.51E+02	2.36E+04	
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	4.42E+05	2	2.21E+05	4.04	0.02	3.02
Within groups	2.30E+07	421	5.47E+04			
Total	2.35E+07	423				

Table 2(g) i_{perc}

Groups	*Number*		*Sum*	*Average*		*Variance*
FPW	*110*		*10.1295*	*0.0921*		*0.0092*
SPW	181		14.2011	0.0785		0.0026
TPW	133		5.3749	0.0404		0.0006
	SQ	*dof*	*MQ*	*F*	*Significance*	*F crit*
Between groups	0.18	2	0.09	24.67	0.00	3.02
Within groups	1.56	421	0.00			
Total	1.74	423				

The matrix reported in Table 3 summarises the main insights of the statistical analysis. In this matrix, we classified the average values of indicators identified by the ANOVA [Tables 2(a)–2(g)], for the three pandemic waves, in MIN, MED and MAX.

Table 3 Comparison of the three pandemic waves by means of the average values of the indicators

	FPW	*SPW*	*TPW*
S_t	MIN	MAX	MED
ICU_t	MIN	MED	MAX
IN_t	MIN	MED	MAX
p_t	MIN	MAX	MED
P_t	MIN	MAX	MED
d_t	MED	MAX	MIN
i_{perc}	MAX	MED	MIN

Given the results provided in Table 3, the SPW can be considered the most aggressive of the three waves, while the FPW was the least aggressive, even though it was the one with the higher percentage of infected people (max i_{perc}). In fact, during this wave we registered the lowest values of ICU_t, S_t and IN_t (though IN_t and S_t differences between the average values of the three pandemic waves were not statistically significant in the ANOVA analysis). This is a surprising result given that it was the first pandemic wave and the country's health system was suddenly caught by the spread of the virus.

4 Discussion and conclusions

The SARS-CoV-2 pandemic is an epochal event in the worldwide landscape. In Italy, we are experiencing that its governance requires that both healthcare managers and the country's government coordinate their efforts to manage the sudden spread of the virus. It has surprised the healthcare system that it was not prepared to rapidly adapt to the surge capacity to support the demand for additional resources during the emergency. The country's government tried to contribute to the control of the spread of the virus by promoting restrictions that reduced the possibility of infections and allowed the lowering of the peaks, letting the health system provide care to all people needing it. In order to facilitate this process, relevant indicators have been collected starting from February

2020 that relate to inpatients, people in ICU, deaths, people isolated at home, and recovered people. These indicators are also published as open data by the PC. Even though epidemiologic models are available to assess the trend of the pandemic using these indicators, they do not take into consideration the non-stationary behaviour of this phenomenon, which makes their use in a real context difficult. From the standpoint of the prediction models, moving averages are reliable, but obviously, they require that the time window used for the predictions is set based on the fluctuations of real data, which makes these models reliable within short time windows or for time series with cyclic behaviour. Based on these premises, we analysed the time series of the three pandemic waves registered in Italy and derived useful information for policymakers. The main results of our work can be summarised as follows:

- we identified the most critical indicators to be monitored during the pandemic to be the percentage of infected people, the number of patients in ICU, and the volume of deaths
- we compared some of the indicators to each other to derive insights for healthcare managers
- we found that some indicators are reliable predictors of some others
- we discovered useful graphic representations of the different indicators that can provide immediate and effective information for healthcare managers.

The practical application of the insights we derived is in the form of indicators/graphs that can be used in the implementation of decision support systems, summarising the current status of the pandemic and allowing healthcare managers to make real-time predictions of the trend itself.

References

Bjørnstad, O.N. et al. (2020) 'Modeling infectious epidemics', *Nature methods*, Vol. 17, No. 5, pp.455–456.

Bosa, I., Castelli, A., Castelli, M., Ciani, O., Compagni, A., Galizzi, M.M. and Vainieri, M. (2021) 'Corona-regionalism? Differences in regional responses to COVID-19 in Italy', *Health Policy*, Vol. 125, No. 9, pp.1179–1187.

Getz, W.M. et al. (2018) 'Modeling epidemics: a primer and numerus model builder implementation', *Epidemics*, Vol. 25, pp.9–19.

Hethcote, H.W. (2000) 'The mathematics of infectious diseases', *SIAM Rev.*, Vol. 42, No. 4, pp.599–653.

ISTAT (2020) *Impatto dell'epidemia covid-19 sulla mortalità: cause di morte nei deceduti positivi a SARS-COV-2*, 16 Luglio, Technical Report [online] https://www.istat.it/it/archivio/245573 (accessed 6 December 2020).

Kumpunen, S. et al. (2022) 'Transformations in the landscape of primary health care during Covid-19: themes from the European region', *Health Policy*, Vol. 126, No. 5, pp.391–397.

Lee, A.C.K. and Morling, J. (2020) 'Coronavirus disease 2019: emerging lessons from the pandemic', *Public Health*, Vol. 186, p.A1.

Pelagatti, M. and Maranzano, P. (2021) 'Assessing the effectiveness of the Italian risk-zones policy during the second wave of COVID-19', *Health Policy*, Vol. 125, No. 9, pp.1188–1199.

Tuckwell, H.C. and Williams, R.J. (2007) 'Some properties of a simple stochastic epidemic model of SIR type', *Mathematical Biosciences*, Vol. 208, No. 1, pp.76–97.

Unruh, L. et al. (2022) 'A comparison of health policy responses to the COVID-19 pandemic in Canada, Ireland, the United Kingdom and the United States of America', *Health Policy*, Vol. 126, No. 5, pp.427–437

Winkelmann, J. et al. (2022) 'European countries' responses in ensuring sufficient physical infrastructure and workforce capacity during the first COVID-19 wave', *Health Policy*, Vol. 126, No. 5, pp.362–372.

Yan, P. (2008) 'Distribution theory, stochastic processes and infectious disease modelling', in *Mathematical Epidemiology*, Chapter 10, pp.229–293, Springer, Berlin, Heidelberg.

Websites

https://lab24.ilsole24ore.com/coronavirus/# (accessed 6 December 2020).