



Research Article

Workforce Sick-Leave as an Early Indication of Increasing COVID-19 Hospitalizations: Sick-Leave Compared with COVID-19 Hospitalizations

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Citation: Jongenotter F, Keet MG, Wisse BW, de Keizer NF, Bakhshi-Raiez F, et al. (2026) Workforce Sick-Leave as an Early Indication of Increasing COVID-19 Hospitalizations: Sick-Leave Compared with COVID-19 Hospitalizations. J Community Med Public Health 10: 571. DOI: <https://doi.org/10.29011/2577-2228.100571>

Received Date: 18 May, 2026; **Accepted Date:** 26 May, 2026; **Published Date:** 29 May, 2026

Abstract

Objectives: The value of workforce sick-leave absenteeism data for infectious disease surveillance is unknown. The time between increased sick-leave and increased hospitalisations might also indicate the time to increased pressure on hospital care. **Methods:** To provide insight into this, we calculated Spearman correlation coefficients at different lags between weekly sick-leave and COVID-19 hospitalization rates during and shortly after the COVID-19 epidemic in the Netherlands (3 March 2020 to 2 July 2023). We analysed SARS-CoV-2 variant periods (wildtype, alpha, delta, omicron) and age groups for hospitalisations (working age: 18-66 years, elderly: 67+ years old). We repeated the analyses on the subset of ICU admissions (12-20% of all hospitalisations). **Results:** Visual inspection showed some coherence, which was more pronounced during the delta and omicron periods for both age groups. Highest correlation coefficients were between lags of -1 to -4 weeks (sick-leave preceding hospitalizations). Highest correlations for the working-age and elderly hospitalizations were during delta (0.90, lag -4; 95%CI [0.79-0.95] and 0.91, lag -2; 95%CI [0.81-0.96], respectively); lowest during alpha (0.53, lag -4; 95%CI [0.14-0.78] and 0.41, lag -4; 95%CI [-0.00-0.71], respectively). Results were similar when restricting analyses to ICU admissions only. **Conclusion:** Workforce sick-leave was associated with COVID-19 hospitalizations and offered a 1-to-4-week earlier indication of potentially increasing hospitalizations and ICU admissions. Sick-leave data may be an additional surveillance source in future epidemics and pandemics to indicate expected increased pressure on hospitals.

Keywords: COVID-19, SARS-CoV-2, Hospitalisations, Sick-leave

Introduction

During the COVID-19 pandemic, workforce sick-leave and infections with severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the virus causing COVID-19, were correlated. Sick-leave trends mostly preceded trends in infections by 1-2 weeks in the Netherlands [1]. Also, recent research showed that SARS-CoV-2 RNA levels measured in wastewater are associated with COVID-19-related sick-leave [2]. Sick-leave data are always readily available and can thus be used at the start of an epidemic or pandemic, when other early indicator surveillance systems such as wastewater surveillance are not available due to not yet developed laboratory testing. However, the association between sick-leave and the more severe endpoint of COVID-19 hospitalizations during the pandemic is not known. This association might provide an additional indication of the value of sick-leave data for surveillance at the beginning of or during outbreaks. Hospitalizations, contrary to lab-confirmed infections, did not depend on varying national testing policies for the general public or on laboratory testing behaviour by individuals, which also varied over time. Hospitalizations are a very relevant societal endpoint given overwhelmed healthcare systems were a major driving force for non-pharmaceutical measures to limit spread of SARS-CoV-2.

The COVID-19 epidemic in the Netherlands started in March 2020 and all measures were lifted in March 2022, which we will refer to as the epidemic period. During the epidemic, patients admitted for severe acute respiratory infections (SARI) were always tested for SARS-CoV-2. Post-epidemic, these admissions were often still tested for SARS-CoV-2, while routine testing in the general population was no longer performed. The optimal lag time between sick-leave and COVID-19 hospitalizations could indicate the time to increased pressure on hospital care. The magnitude of the correlation could indicate the hospital burden of an increase in the circulation of SARS-CoV-2. Therefore, to understand the potential worth of sick-leave data as an additional surveillance data source for new outbreaks we studied the association and lag time between sick-leave and all COVID-19 hospitalizations and Intensive Care Unit (ICU) only admissions during and shortly after the COVID-19 epidemic in the Netherlands.

Methods

For the period of 3 March 2020 until 2 July 2023, we explored trends of weekly all-cause workforce sick-leave data and national weekly COVID-19 hospital and ICU-only admissions. During the post-epidemic period there was still high SARS-CoV-2 circulation and collection of data continued. The study period ends 2 July 2023, when the number of hospitals providing COVID-19 admis-

sion data became less complete. This was also just before the summer holidays when sick-leave generally decreases. The sick-leave data is registered by HumanTotalCare (HTC), a nationwide Dutch occupational health service [3], which covers approximately 11% of the Dutch working population as defined by Statistics Netherlands [4]. Using the first day of sick-leave and the coverage of employers contracting HTC services, we calculated weekly incidences. The dataset almost entirely consisted of people of working age, which is generally 18-66 in the Netherlands. The hospital data was registered by the National Intensive Care Evaluation (NICE) foundation, which registers ICU admissions to improve the quality of ICU care and had a nationwide coverage during the study period for all COVID-19 hospital admissions (wards and ICU) [5].

Trends were inspected visually and Spearman correlations were calculated at different weekly lag times (-4 to +4 weeks), between sick-leave notifications and 1) COVID-19 hospital admissions (including ICU admissions) and, for further disease severity, 2) restricted to COVID-19 ICU-only admissions. The lag with the highest correlation coefficient was considered the optimal lag time. As previously described, the sick-leave incidence was interpolated for the sharp dips during the Christmas holidays, and not so for the longer summer holidays with less sharp dips [1]. As older individuals were hospitalized due to COVID-19 more often than younger individuals we distinguished between two age groups: hospitalizations of working-age population (ages 18-66 years), and elderly hospitalizations (ages 67+ years). We were not able to stratify between these age groups in the sick leave data, but with very few elderly in the Dutch workforce, this dataset consisted almost entirely of people of working age (18-66). Age-specific hospital data was therefore always correlated with the sick-leave data of the total working population. Furthermore, we also distinguished between SARS-CoV-2 variant periods (wildtype, alpha, delta and omicron dominance) [6].

- Wildtype: 02 March 2020 until 31 January 2021
- Alpha: 01 February 2021 until 04 July 2021
- Delta: 05 July 2021 until 02 January 2022
- Omicron: 03 January 2022 until 02 July 2023

Results

The mean incidence during the total study period for sick-leave was 1183 per 100000 working inhabitants (Table 1). The highest incidence occurred during the omicron period (1411 per 100000). The mean incidence during the total study period of all COVID-19 hospital and ICU-only admissions was 2.92 and 0.58 per 100 000 (ages 18-66) and 15.10 and 1.69 per 100000 (ages 67+) inhabitants respectively. For both age groups, the highest incidence occurred during the alpha period for both all hospitalizations and ICU-only

admissions, at 5.32 and 1.18 per 100000 for the working population and 16.89 and 2.98 per 100000 for the elderly population respectively.

	Total period	Wildtype period	Alpha period	Delta period	Omicron period
Sick-leave incidence per 100 000 workers	1183	939	914	1176	1411
All hospital admissions incidence per 100 000 inhabitants (ages 18-66)	2.92	3.31	5.32	3.59	1.80
ICU-only admissions incidence per 100 000 inhabitants (ages 18-66)	0.58	0.78	1.18	0.87	0.18
All hospital admissions incidence per 100 000 inhabitants (ages 67+)	15.10	16.66	16.89	14.57	13.81
ICU-only admissions incidence per 100 000 inhabitants (ages 67+)	1.69	2.62	2.98	1.70	0.76

Table 1: Average incidence of reports of sick-leave and COVID-19 hospital and ICU admissions per week during the study period. All hospital and ICU-only admissions are stratified per age group (ages 18-66 and 67+ years).

Visual inspection of the time series showed some coherence between sick-leave and COVID-19 hospital and ICU admissions, more visibly pronounced during the delta and omicron period for both age groups (Figures 1 and 2). In these two periods, the sick-leave rates visually seem to increase before the hospital and ICU admissions incidence, which is reflected by the negative lags of the highest correlation coefficients stratified by time-period (Table 2).

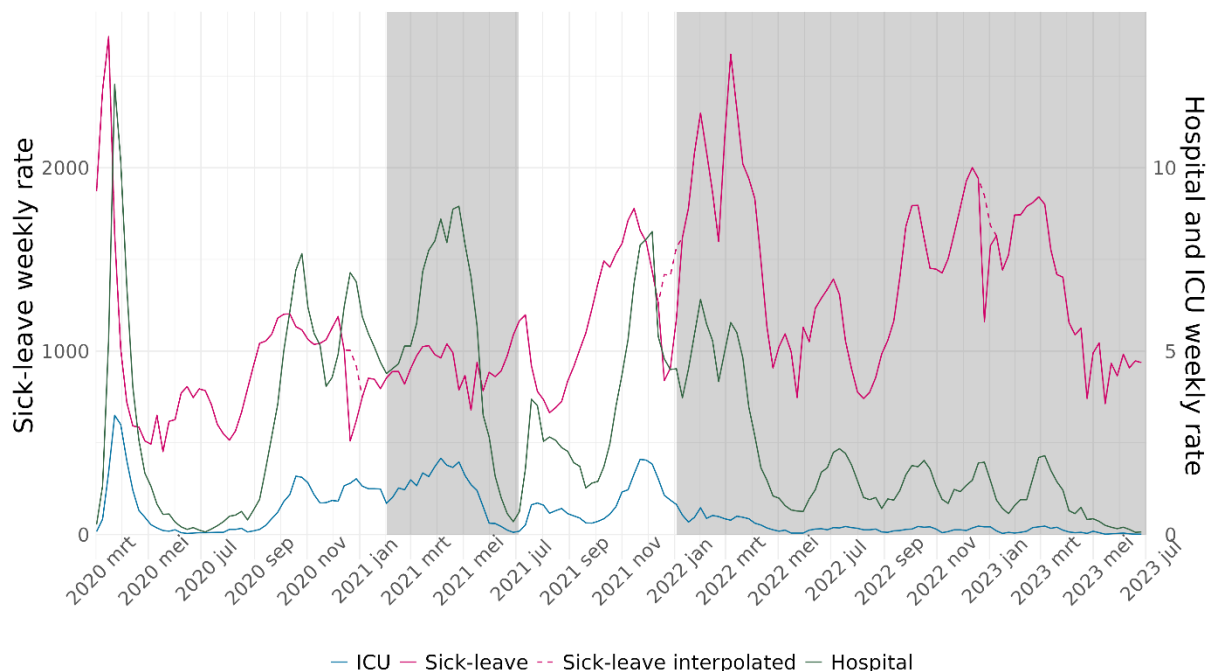


Figure 1. Sick-leave and COVID-19 hospital and ICU admission incidence per 100.000 per week. Red dashed line: sick-leave is interpolated during Christmas holidays. White and grey shading: the periods of SARS-CoV-2 variants are shown with alternating shaded planes (wildtype, alpha, delta, omicron). Hospitalizations of ages 18-66.

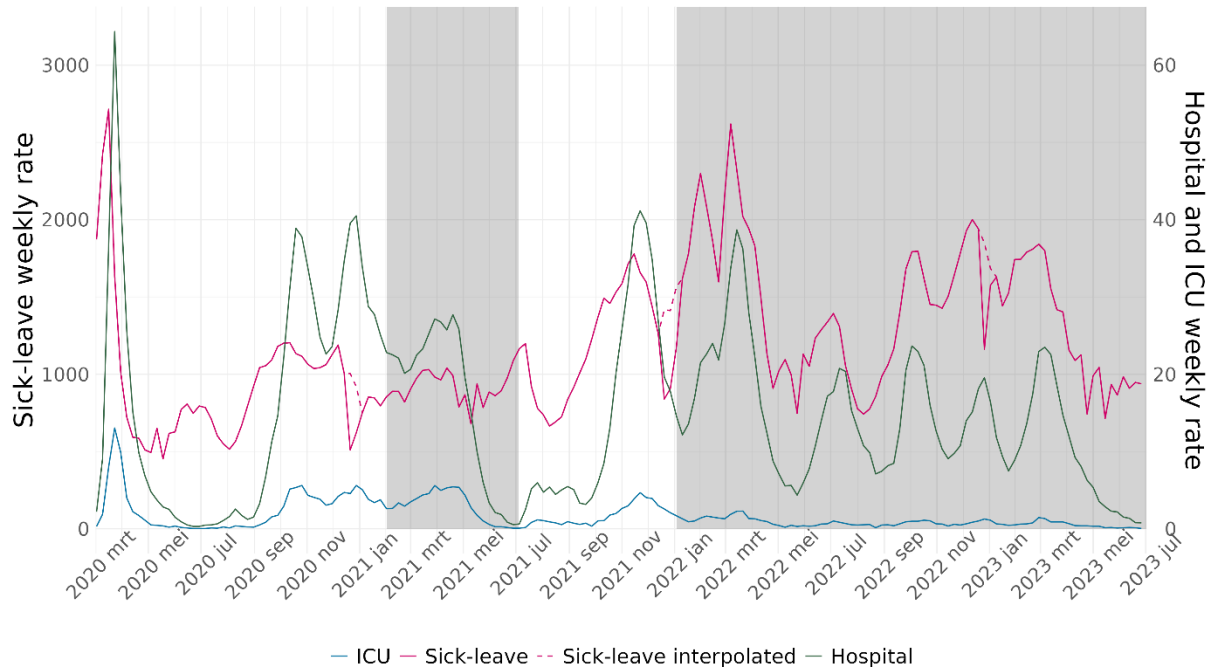


Figure 2. Sick-leave and COVID-19 hospital and ICU admission incidence per 100.000 per week. Red dashed line: sick-leave is interpolated during Christmas holidays. White and grey shading: the periods of SARS-CoV-2 variants are shown with alternating shaded planes (wildtype, alpha, delta, omicron). Hospitalizations of ages 67+.

	Total period		Wildtype period		Alpha period		Delta period		Omicron period	
	Optimal lag	Correlation coefficient	Optimal lag	Correlation coefficient	Optimal lag	Correlation coefficient	Optimal lag	Correlation coefficient	Optimal lag	Correlation coefficient
All hospital admissions (ages 18-66)	-2	0.35, 95% CI [0.21, 0.47]	-3	0.82, 95% CI [0.69, 0.89]	-4	0.53, 95% CI [0.14, 0.78]	-4	0.90, 95% CI [0.79, 0.95]	-1	0.73, 95% CI [0.61, 0.82]
ICU-only admissions (ages 18-66)	-2	0.16, 95% CI [0.02, 0.30]	-3	0.82, 95% CI [0.70, 0.90]	-4	0.48, 95% CI [0.07, 0.75]	-3	0.75, 95% CI [0.52, 0.88]	-1	0.71, 95% CI [0.57, 0.80]
All hospital admissions (ages 67+)	-2	0.59, 95% CI [0.49, 0.68]	-3	0.80, 95% CI [0.67, 0.88]	-4	0.41, 95% CI [-0.00, 0.71]	-2	0.91, 95% CI [0.81, 0.96]	-1	0.81, 95% CI [0.72, 0.88]
ICU-only admissions (ages 67+)	-2	0.38, 95% CI [0.25, 0.50]	-3	0.82, 95% CI [0.70, 0.89]	-4	0.44, 95% CI [0.03, 0.73]	-3	0.93, 95% CI [0.84, 0.97]	-1	0.85, 95% CI [0.78, 0.90]

^aThe optimal lag is the lag with the highest correlation coefficient (negative lags: sick-leave preceded COVID-19 hospitalizations, positive lags: sick-leave followed COVID-19 hospitalizations).

Table 2: Correlation coefficients at optimal lags in weeks ^a between sick-leave and all COVID-19 hospital and ICU-only admissions specifically during the study period per age group (ages 18-66 and 67+ years).

The highest correlation coefficients between sick-leave and all or ICU-only hospitalizations were during the delta period: for the younger age group (18-66 years) being 0.90 and 0.75 for all and ICU-only hospitalizations respectively, for the elderly age group (67+ years) these were 0.91 and 0.93. The lowest correlation coefficients were observed during the total period for the 18-66 years old group, at 0.35 and 0.16 for all and ICU-only hospitalizations. As previously mentioned, we considered the lag where the correlation coefficient is highest, as the optimal lag time. The optimal lag time between sick-leave and hospitalizations and ICU admissions varied per period, the shortest being during omicron with an optimal lag of -1 (i.e., the sick-leave incidence one week before COVID-19 hospitalizations showing the highest correlation coefficient), and longest being lag of -4 during the alpha and delta periods. Generally, both the correlation coefficient and optimal lag time within a period were quite similar between age groups and hospitalization types.

Discussion

Trends in sick-leave were correlated with and preceded all COVID-19 hospitalizations as well as ICU-only admissions. The optimal lag time varied by SARS-CoV-2 variant time period, but was always negative. This implies that sick-leave might offer a 1-to-4-week earlier indication of increasing hospitalizations, potentially providing early insight into increasing pressures on hospital care as well as on ICU care.

The correlations of the total period were much lower than the correlations for the separate variant periods. This suggests that the correlation between work sick-leave and COVID-19 hospital and ICU-only admissions is dependent on the type of dominant SARS-CoV-2 variant, which differed in infectiousness and severity, population immunity, both infection-induced and by vaccination, and seasonal influences. As for vaccination coverage, there were four different vaccination campaigns during the study period. The first and second dose programme began at the end of the wildtype period (January 2021), where first the elderly and healthcare workers were prioritized for vaccination before other vaccine recipients. Vaccination continued through the alpha period (until July 2021). In November 2021 (the end of the delta period), the programme for the booster vaccination started, and in March and September 2022 (during the omicron period) specific groups (people aged 60 years and older and specific high-risk groups of any age) were invited to receive the booster vaccination [7]. The differing immunity over the study period is expected to explain the lower correlation coefficients for the total and alpha periods. Throughout the total study period, the SARS-CoV-2 seroprevalence (i.e. the percentage of individuals having antibodies) in the population changed from zero to over 95% [8]. Because vaccination primarily protected against severe disease and related hospitalization and to a lesser extent

against infection [9,10], correlation coefficients will be impacted when they are calculated over a period that overlaps with changing population immunity. As the vaccine was rapidly introduced into a largely naive population during the alpha period, the same effect can be expected during this period specifically. We found higher correlation coefficients when restricting the alpha period to a shorter window where persons aged 18-66 were not yet vaccinated [7] (Table 3), compared to the entire alpha period correlation coefficient. These were also more similar to the correlation coefficients in other periods.

	Alpha period	
	Optimal lag	Correlation coefficient
All hospital admissions (ages 18-66)	-1	0.86, 95% CI [0.49, 0.97]
ICU-only admissions (ages 18-66)	-2	0.89, 95% CI [0.58, 0.97]

Table 3: Correlation coefficients at optimal lags between sick-leave and all COVID-19 hospital and ICU-only admissions specifically during the adjusted alpha period (1 February 2021 to 10 April 2021, during which persons aged 18-66 were not yet vaccinated) for ages 18-66.

During all variant periods, the correlation coefficients were comparable with those reported between sick-leave and the less severe indicator of SARS-CoV-2 infection notifications, but the lag time to hospitalizations was longer [1]. The optimal lag times per variant-period were larger than those reported between sick-leave absenteeism and infections at -1 (omicron) to -4 (alpha) compared to +1 to -2 during the same periods [1]. Since COVID-19 hospitalizations can only occur after infection, a longer time between sick-leave and hospitalizations is expected than between sick-leave and SARS-CoV-2 infection notification date. Additionally, an infection pattern where first younger age-groups were infected, who then infected older age-groups [11], who were much more likely to be hospitalized, would increase the lag time. However, the level of delay was shorter during the omicron period, which had a lag time between sick-leave and hospitalizations of -1. Infection pressure was much higher during that time and a previous study showed that the (mostly) milder endpoint of SARS-CoV-2 infection notifications were actually leading sick-leave [1] by one week during omicron circulation.

Uniquely, we could study the association during periods (wildtype, alpha and delta specifically) where mostly a single respiratory viral pathogen circulated (SARS-CoV-2), as the control measures in place during large parts of the COVID-19 pandemic reduced the

circulation of other pathogens [12] (only RSV surveillance showed RSV circulation from summer 2021 onwards [13]; influenza virus circulation re-started during the omicron period). We cannot rule out entirely however that other infections or factors played a role in sick-leave during the COVID-19 epidemic. Sick-leave is a syndromic indicator and is thus not specific to any (respiratory) infectious disease. When multiple pathogens are co-circulating, which is common outside of the COVID-19 pandemic period, work sick-leave may not largely reflect the effect of a single pathogen.

The study data had multiple strengths. The coverage of the working population (at ~11%), the inclusion of all hospitals in The Netherlands [5] and the availability of the sick-leave data throughout the study period. These data are consistently collected, and can be used when other surveillance systems, such as specific testing, general practitioner sentinel networks or wastewater surveillance are not available or disrupted. Laboratory diagnostic testing specifically may require time to develop or expand capacity for when a new pathogen arises. Another strength is that COVID-19 hospitalizations were not as directly impacted by changing behaviour of people and changing policies as testing was during the epidemic. This makes the correlation with sick-leave possibly more reliable throughout the study period compared to the correlations with SARS-CoV-2 infection notifications. Although during periods where the pressure on hospitals was very high, especially during the first months of the epidemic, the number of hospitalizations may have been lower than what would have been the case when there would have been enough capacity. Additionally, sick-leave was likely influenced by changing measures imposed to control the pandemic, such as the advice to work from home [14]. For jobs where work from home was not possible, sick-leave would increase despite symptoms being mild. For jobs where work from home was possible, the opposite might occur if infections were mild and sick-leave would not increase despite possible infections. During certain periods, multiple industries were directly affected by measures taken by the government. For example, entertainment and hospitality industries were effectively shut down multiple times throughout the pandemic. These situations are likely to have impacted the number of sick-leave reports, possibly reducing the actual correlation.

In conclusion, sick-leave absenteeism was associated with both all COVID-19 hospitalizations and with COVID-19 ICU-only admissions in a period wherein control measures were in place. To understand the association between sick-leave and SARI hospitalizations outside of pandemic situations, it would be beneficial to investigate this association throughout post-COVID-19 pandemic respiratory seasons. To help shed light on the additional use of sick-leave data as a routine syndromic surveillance source for viral

respiratory infections it would also be beneficial to compare sick-leave data to other timely data sources, such as citizen science data or sewage surveillance. One such citizen science initiative in the Netherlands that could be used for this comparison continuously collects data on multiple circulating viral respiratory infections in the general population [15].

Acknowledgements

We would like to acknowledge the effort of all Dutch hospitals to record their COVID-19 patients daily and additionally all the ICUs that also collected the comprehensive clinical data of the COVID-19 patients to NICE-database. Without their effort this study would not have been possible. We also like to thank all employees of NICE Research & Support for the technical development of the COVID-19 Online Module, processing the data, and support under high work pressure.

Conflict of Interest

- Femke Jongenotter: none declared.
- Martijn G. Keet: none declared.
- Bram W. Wisse: is employed by HumanTotalCare.
- Nicolette F. de Keizer and Ferishta Bakhshi-Raiez: the department they work for received funding from the Ministry of Health, Welfare and Sport to process ICU and hospital data due to COVID-19 admissions. The NICE foundation pays the department for processing clinical and patient outcome data from all Dutch ICUs into quality improvement information.
- Dylan W. de Lange: is secretary of the board of the NICE foundation.
- Dave A. Dongelmans: is chair of the NICE foundation.
- Arianne B. van Gageldonk-Lafeber: none declared.
- Liselotte van Asten: none declared.

Funding

This study was funded from the regular budget of the Centre for Infectious Disease Control made available by the Ministry of Health, Welfare and Sport, the Netherlands.

Data Availability Statement

The sick-leave dataset underlying this study are not publicly available as they are owned by a third party (HumanTotalCare, HTC). On reasonable request the dataset used for this study can be requested from HTC. The metadata of the SARS-CoV-2 dataset underlying this study are publicly available at [RIVMdata](#).

Citation: Jongenotter F, Keet MG, Wisse BW, de Keizer NF, Bakhshi-Raiez F, et al. (2026) Workforce Sick-Leave as an Early Indication of Increasing COVID-19 Hospitalizations: Sick-Leave Compared with COVID-19 Hospitalizations. *J Community Med Public Health* 10: 571. DOI: <https://doi.org/10.29011/2577-2228.100571>

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