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ORIGINAL CONTRIBUTION

Utility of prehospital call center ambulance dispatch data for COVID-19 cluster surveillance: A retrospective analysis

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Abstract

Introduction: Cluster surveillance, identification, and containment are primary outbreak management techniques; however, adapting these for low- and middle-income countries is an ongoing challenge. We aimed to evaluate the utility of prehospital call center ambulance dispatch (CCAD) data for surveillance by examining the correlation between influenza-like illness (ILI)-related dispatch calls and COVID-19 cases.

Methods: We performed a retrospective analysis of state-level CCAD and COVID-19 data recorded between January 1 and April 30, 2020, in Telangana, India. The primary outcome was a time series correlation between ILI calls in CCAD and COVID-19 case counts. Secondarily, we looked for a year-to-year correlation of ILI calls in the same period over 2018, 2019, and 2020.

Results: On average, ILI calls comprised 12.9% (95% CI 11.7%–14.1%) of total daily calls in 2020, compared to 7.8% (95% CI 7.6%–8.0%) in 2018, and 7.7% (95% CI 7.5%–7.7%) in 2019. ILI call counts from 2018, 2019, and 2020 aligned closely until March 19, when 2020 ILI calls increased, representing 16% of all calls by March 23 and 27.5% by April 7. In contrast to the significant correlation observed between 2020 and previous years' January–February calls (2020 and 2019—Durbin-Watson test statistic [DW] = 0.749, $p < 0.001$; 2020 and 2018—DW = 1.232, $p < 0.001$), no correlation was observed for March–April calls (2020 and 2019—DW = 2.012, $p = 0.476$; 2020 and 2018—DW = 1.820, $p = 0.208$). In March–April 2020, the daily reported COVID-19 cases by time series significantly correlated with the ILI calls (DW = 0.977, $p < 0.001$). The ILI calls on a specific day significantly correlated with the COVID-19 cases reported 6 days prior and up to 14 days after (cross-correlation > 0.251, the 95% upper confidence limit).

Conclusions: The statistically significant time series correlation between ILI calls and COVID-19 cases suggests prehospital CCAD can be part of early warning systems aiding outbreak cluster surveillance, identification, and containment.

KEYWORDS

cluster, hotspot, outbreak surveillance, surveillance

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INTRODUCTION

Cluster detection remains a critical COVID-19 containment strategy, and surveillance helps cluster detection.[1,2] Low- and middle-income countries (LMICs) witnessed a slower COVID-19 vaccination rate and a higher socioeconomic impact of lockdowns, highlighting the need for early detection and optimal containment duration.[3–5] The World Health Organization (WHO) emphasizes the continued importance of surveillance in pandemic management.[6] Limited prior research has suggested the utility of ambulance dispatch data for early detection and disease surveillance.[7–10] Though common in high-income countries, ambulance dispatch systems continue to evolve in LMICs, and there is scant research on whether LMICs could use ambulance dispatch data for surveillance.

With its size and reach, India's prehospital emergency medical services (EMS) system, with a buffer capacity to manage over half a million emergency response calls daily and over 28,000 emergency response vehicles, can serve as an archetype for other LMICs.[11] All 35 states/union territories have a call center ambulance dispatch (CCAD) type with 108 or 102 as emergency response numbers operating under a public–private partnership.[12] Fever and difficulty breathing are part of the standardized reasons for ambulance dispatch within the CCAD, which aligns with the COVID-19 symptoms commonly reported early in the pandemic of fever (98%), cough (76%), and dyspnea (55%).[13,14]

We hypothesized that the incidence of COVID-19 or an influenza-like illness (ILI) would increase the calls for ambulance dispatch and sought to investigate whether CCAD could be used effectively for surveillance. To do so, we used a CCAD database from a state-based EMS system in India to examine the correlation between COVID-19 cases reported and ambulance dispatch requests.

METHODS

Overview

This study is a retrospective analysis of ILI calls received between January 1 and April 30, 2018, 2019, and 2020, and the COVID-19–positive cases registered between January 1 and April 30, 2020, in Telangana, India. We selected Telangana as it was one of the earliest states to report COVID-19 cases.

Setting

We based this study at the GVK Emergency Management and Research Institute, India's largest prehospital care provider. It began its operations in 2005 with 30 ambulances and one CCAD at Hyderabad, Telangana. At the time of this study, its operations included 17 state-level units, each with a dedicated CCAD, ambulance operations, and an emergency medical technician training division catering to the entire state under a public–private partnership. These 17 states were home to almost 60% of the country's population. The operations team placed ambulances strategically across the state, and CCAD located the nearest ambulance to respond to requests. The CCAD worked 24 h daily and routinely answered over 200,000 calls with a buffer capacity to manage over half a million daily calls. The personnel posted there received in-house training before induction. The reasons for ambulance dispatch, also termed chief complaints by the CCAD, were a predefined list. The personnel at CCAD collected information volunteered by the caller and categorized the call into one of the predefined chief complaints. At the time of this study, the dispatch did not change any key questions to identify possible ILI.

Data definitions

From the CCAD, we extracted the variables of the date-time call received, the chief complaint, and the place of call origin. We defined ILI calls as those with a documented chief complaint of fever, difficulty breathing, or suspected COVID-19 indicated by the caller to request the ambulance. To observe the effects of COVID-19 on the ILI calls, we split the CCAD data into January–February and March–April data sets for time series comparison.

The COVID-19 data set was from a crowdsourced and aggregated online database (data available at api.covid19india.org). This database contains COVID-19–positive cases by the district in Telangana from February 1 through April 30, 2020. Telangana reported the first case of COVID-19 on March 2, 2020.

Outcome measures and data analysis

The primary outcome measure is the time-lagged correlation between the daily COVID-19 case count and the ILI call count in March and April 2020. Specifically, we aimed to look for the duration of correlation between ILI call counts and COVID-19 case counts, that is, how many days back in time and into the future ILI call counts correlated with the COVID-19 case counts, and the direction of correlation, that is, whether the ILI calls decreased or increased with COVID-19. We used cross-correlation function, a time-lagged cross-correlation, to do this. By moving one of the variables relative to the other in time, it analyzes whether a change in one variable is followed by a change in another variable and shows its directionality and duration on a timeline.[15,16] In this study, we looked for a correlation between the ILI calls received on a specific day and COVID-19 cases reported up to 3 weeks earlier and 3 weeks later. We moved the COVID-19 count relative to the ILI call count. This test does not necessarily reflect causality.

The secondary outcome measures are the daily call volume trends and the correlation between ILI call counts by year (2020 vs. 2018, 2020 vs. 2019). We used mean proportions and a 95% confidence interval (CI) to report daily call volume trends each year. We derived the proportion of daily all-cause ambulance requests that were ILI-based and calculated its mean and 95% CI for each year

(2018, 2019, and 2020). We used the Durbin-Watson test statistic (DW) to check the correlation between ILI call counts by year (2020 vs. 2018, 2020 vs. 2019). Our aim was to see if current year call counts correlate with and depend on previous year call counts. A serial correlation of residuals from a regression analysis of two variables in time series indicates a time series correlation, which means that the present calls correlate with calls from a similar point of time in the past.[17,18]

We used R v.3.5.1 in RStudio v.1.1.447 (RStudio, Inc.) for data analysis. The institutional review board at Stanford University waived approval as the study did not involve human subjects.

RESULTS

ILI call volumes between January 1 and April 30, 2020, were 70% higher than in 2019 and 54% higher than in 2018 (Table 1). In 2020, the proportional contribution of ILI calls to total daily calls was significantly higher compared to 2018 and 2019 (Table 1). ILI calls from 2018, 2019, and 2020 aligned closely from January 1 until March 19, contributing 9%–10% of daily calls. After March 19, ILI calls in 2020 quickly constituted a disproportionately higher percentage of total calls, representing 16% of all calls by March 23 and 27.5% by April 7 (Figure 1).

A significant correlation was observed between the 2020 and 2018 time series and between the 2020 and 2019 time series in the January–February data sets. However, it is absent in the March–April data sets (Table 2).

The rise of COVID-19 cases parallels the change in ILI call counts in March and April 2020. The first COVID-19–positive case was on March 2, and the cumulative count was 1116 by April 30. The COVID-19 case count showed a slight uptick on March 14, which was followed by a sharp spike in ILI calls on March 19, which in turn was followed by a steep rise in COVID-19 cases after approximately 10 days on March 28 (Figure 1). The COVID-19 case count had a significant time series correlation with 2020 calls from the March–April data set (DW = 0.977, $p < 0.001$). The ILI calls on a specific day significantly correlated with the COVID-19 cases reported 7 days prior and up to 14 days after (Figure 2; cross-correlation > 0.251, the 95% upper confidence limit).

DISCUSSION

Our analysis demonstrated that the emergence of COVID-19 was associated with a significant increase in calls for emergency ambulance dispatch for ILI symptoms (documented chief complaint of fever, difficulty breathing, or suspected COVID-19). Furthermore, COVID-19 disrupted the existing time series correlation of ILI calls observed in preceding years.

Our analysis also demonstrated that above-average COVID-19 cases are associated with above-average ILI calls up to 7 days later. Simultaneously, above-average ILI calls are associated with above-average COVID-19 cases up to 14 days later. The duration between the increase in COVID-19 and spikes in ILI call volume appears consistent with expectations that nearly all infected persons with symptoms will present as symptomatic within 12 days of infection.[19] The temporality of these findings fit well within the clinical characteristics of the COVID-19 variant prevalent during this study period, namely, a reported incubation period of 5–12 days, the infective

TABLE 1 ILI calls registered between January 1 and April 30, in the years 2018, 2019, and 2020

ILI calls	2018	2019	2020
Between January and April	11,635	10,494	17,861
As a proportion of daily calls	7.8% (95% CI 7.6–8.0)	7.7% (95% CI 7.5–7.7)	12.9% (95% CI 11.7–14.1)

Abbreviation: ILI, influenza-like illness.

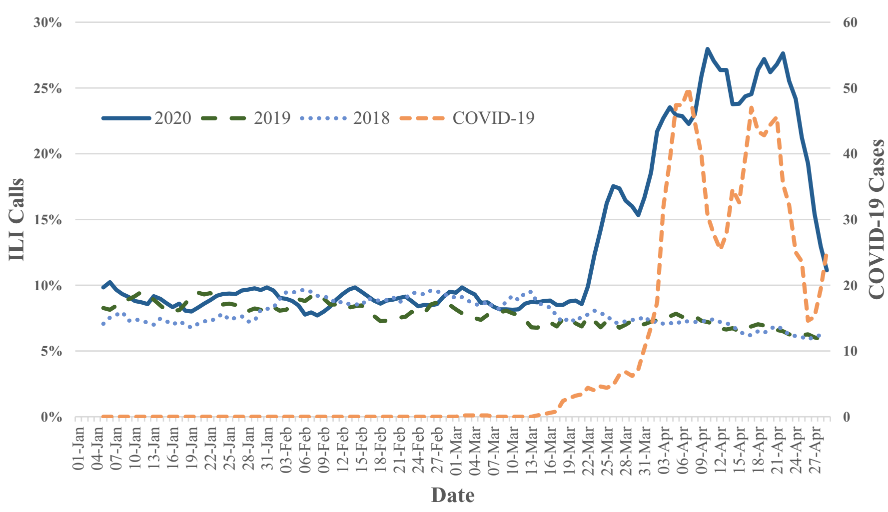

FIGURE 1 Proportion of total calls represented by ILI calls and the COVID-19 cases reported. Number of ILI calls (left axis) by year (2020, solid line; 2019, large dashed line; 2018, dotted line). COVID-19 calls (right axis) in 2020 (small dash line). ILI, influenza-like illness.

TABLE 2 Durbin-Watson test statistics[a]

	2020 vs. 2018	2020 vs. 2019	2020 vs. COVID-19
Jan–Feb	1.232 ($p < 0.001$)	0.749 ($p < 0.001$)	
Mar–Apr	1.820 ($p = 0.208$)	2.012 ($p = 0.476$)	0.977 ($p < 0.001$)

[a]DW (p-value).

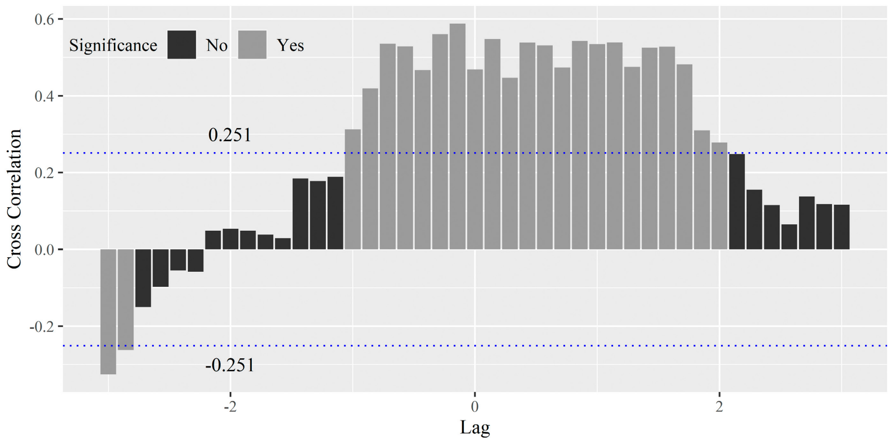

FIGURE 2 A cross-correlation of COVID-19 cases and ILI calls. Each lag is 7 days. Dotted lines represent the upper and lower 95% confidence limits; bars crossing these lines are statistically significant. ILI, influenza-like illness.

period starting 2–3 days presymptomatic and lasting up to 10 days postsymptomatic and the likelihood of a test turning positive 3–5 days postexposure.[19,20]

These findings support the use of CCAD as a viable data source for cluster surveillance of COVID-19 and potentially other infectious disease outbreaks. This finding is in line with early-phase research looking at this system's CCAD data from 2010 that demonstrated the existence of near real-time signals within this data set that served as an early warning of a Dengue fever outbreak.[7] Similarly, previous studies using similar ambulance dispatch data from other countries has shown the utility of this data type in detecting severe acute respiratory infections (SARS) and other ILIs.[8–10] For example, a retrospective review of nearly 0.3 million ambulance dispatches recorded a statistically significant rise in respiratory syndrome-related dispatch calls with a weekly increase of one ILI case per 10,000 inhabitants.[8] Thus, our analysis supports previous reports indicating that in countries with centralized EMS and electronic call center data collection, the CCAD may be valuable in timely infectious disease outbreak cluster detection for COVID-19 and other acute febrile illnesses of high importance. This evidence is the first of its kind to emanate from an LMIC as the COVID-19 pandemic made its inroads, and it is potentially applicable across similar sociocultural geographies at the least.

During the COVID-19 pandemic, surveillance efforts to detect clusters and monitor the disease burden have informed public health efforts. In the initial phases of the pandemic, when COVID-19 made inroads as clusters, the probability of controlling the COVID-19 outbreak decreased with delayed isolation post-symptom onset, fewer cases traced, and an increased transmission before symptom onset.[1] Two years into the pandemic, the WHO emphasized monitoring hospitalizations and intensive care unit admissions as one of the core surveillance objectives.[6] While this analysis demonstrates the potential of the CCAD in infectious disease surveillance, in circumstances where patients primarily request an ambulance when severely symptomatic, the CCAD may only capture a proportion of the disease burden as only 15% of COVID-19–positive cases develop severe symptoms.[21] However, even in geographies with mature emergency care systems, less than 25% of all-cause ambulance requests are reported to have an acuity of emergent or higher.[22] Most COVID-19 patients develop difficulty breathing about 8 days into the symptomatic period.[21] As a result, the CCAD might record the signal of a COVID-19 outbreak up to a week into cluster development and may not accurately capture the additional burden due to the secondary spread of infection. While this timeline limits public health utility for very early detection of COVID-19, the CCAD-based system would be a valuable independent surveillance data source to monitor the COVID-19 pandemic's course by providing some estimate of disease burden and hospitalization, potentially helping with the allocation of valuable resources. Further, the CCAD may prove more or less beneficial in future infectious disease outbreaks with different symptom onset and transmission characteristics.

Spatial analysis by overlaying the variables studied here on geospatial coordinates would aid in detecting hotspots. Given a random distribution of events in space, a spot with a higher concentration of events than expected is defined as a hotspot. Hotspot analysis is central to a CCAD-based early warning system, and a space–time scan statistic has proven beneficial in monitoring COVID-19 hotspots.[23] At the time of this study, a CCAD-based system that gives real-time public health inputs was not in place in India.

LIMITATIONS

Like all retrospective analyses, we are limited to detecting correlation. Our population-level analysis was not designed to establish a relationship between the ILI call and COVID-19 illness in the same person. Moreover, the database used did not store laboratory evidence of COVID-19 confirmation. The geographic area considered for the study was large, and it is possible there were isolated pockets within this area with ILI activity but little to no COVID-19 exposure.

CONCLUSION

In conclusion, the prehospital call center ambulance dispatch shows promise in detecting outbreaks of COVID-19, and ambulance dispatch data may be a valid strategy for influenza-like illness surveillance in low- to middle-income countries. Future research is necessary to confirm these findings and better understand how such a system could be best implemented.

AUTHOR CONTRIBUTIONS

Matthew C. Strehlow, Ramana G.V. Rao, Jennifer A. Newberry, Michael A. Kohn, and Srinivasa R. Janagama contributed to the study design, implementation, and manuscript production. Srinivasa R. Janagama, Jennifer A. Newberry, and Michael A. Kohn contributed to the data analysis.

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CONFLICT OF INTEREST

GVR is a full-time employee of the GVK Emergency Management Research Institute, which operates the ambulance services studied here. The other authors declare no potential conflict of interest.

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