Original Article

Modelling the Utility of Body Temperature Readings From Primary Care Consults for SARS Surveillance in an Army Medical Centre

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Abstract

Introduction: There is interest in surveillance systems for outbreak detection at stages where clinical presentation would still be undifferentiated. Such systems focus on detecting clusters of syndromes in excess of baseline levels, which may indicate an outbreak. We model the detection limits of a potential system based on primary care consults for the detection of an outbreak of severe acute respiratory syndrome (SARS). Materials and Methods: Data from an averaged-sized medical centre were extracted from the Patient Care Enhancement System (PACES) [the electronic medical records system serving the Singapore Armed Forces (SAF)]. Thresholds were set to 3 or more cases presenting with particular syndromes and a temperature reading of ≥38°C (T ≥38). Monte Carlo simulation was used to insert simulated SARS outbreaks of various sizes onto the background incidence of febrile cases, accounting for distribution of SARS incubation period, delay from onset to first consult, and likelihood of presenting with T ≥38 to the SAF medical centre. Results: Valid temperature data was available for 2012 out of 2305 eligible syndromic consults (87.2%). T ≥38 was observed in 166 consults (8.3%). Simulated outbreaks would peak 7 days after exposure, but, on average, signals at their peak would consist of 10.9% of entire outbreak size. Under baseline assumptions, the system has a higher than 90% chance of detecting an outbreak only with 20 or more cases. Conclusions: Surveillance based on clusters of cases with T ≥38 helps reduce background noise in primary care data, but the major limitation of such systems is that they are still only able to confidently detect large outbreaks.

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Key words: Communicable diseases, Emerging, Epidemiology, Military medicine, Syndrome

Introduction

There has been increasing interest in building surveillance systems capable of detecting outbreaks of infectious diseases, at the stage where clinical presentation would still be undifferentiated. The thrust of such systems is to detect both intentionally induced and naturally occurring outbreaks in their earliest stages, and if possible, at first presentation. These systems have been broadly referred to as syndromic surveillance systems. However, the utility of such systems in early outbreak detection has not been validated,[1] and it has been argued that clinical recognition of cases may precede signals from such systems.[2]

During the outbreak of severe acute respiratory syndrome (SARS) in Singapore,[3] much emphasis was placed on fever symptoms and body temperature readings as a screening tool.[4] Studies have found that more than 80% of SARS cases have a fever of 38°C or more (T ≥38) at presentation.[5] Post-SARS, the Ministry of Health (MOH) essentially set in place a syndromic surveillance system for SARS; the system uses clusters of febrile illness in staff and inpatients as surveillance signals.[6] One study has alluded to the high degree of background noise inherent in such a system, but notes that surveillance for SARS using febrile illness in sick staff may still be viable, at least in the setting of a healthcare environment.[7] However, that study was unable to estimate what size of outbreak could be confidently detected by the system.

Comparisons can be drawn between staff in healthcare institutions and soldiers in the Singapore Armed Forces (SAF). Both are groups of healthy workers operating within well-defined functional units. However, the risk of disease and the baseline rates of febrile illness would be

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different in the setting of the SAF. Moreover, there is a need to know how confident one can be of detecting an outbreak should a case of SARS be introduced into an army camp.

This paper will critically assess if a workplace syndromic surveillance system, based on the detection of clusters of febrile illness in soldiers, would be viable for the purposes of post-epidemic SARS surveillance in the SAF. We also model the detection limits of such system.

Materials and Methods

We analysed a set of primary care data for which temperature readings were readily available, simulated how exposure to this virus would present to a typical army medical centre within the SAF, and estimated the sensitivity of the outbreak detection system to SARS outbreaks of various sizes.

Data Sources

Background surveillance data for the study came from the Patient Care Enhancement System (PACES), the universal electronic medical records system of the SAF. Medical consult data from an average medical centre were extracted for the period from 1 January 2002 through 31 December 2002. Data elements included date of consult, temperature at consultation, and diagnosis codes. Diagnoses in the system, which are coded by the ICD-9 Clinical Modification system, were mapped to disease syndromes by the classification system used in ESSENCE-I (Electronic Surveillance System for the Early Notification of Community-based Epidemics).[8]

Only acute consults for "respiratory", "gastrointestinal" and "fever" syndromes were included, as these represent the possible range of presentations for SARS.[5,9] This also allowed us to be as inclusive as possible, in keeping with the surveillance case definitions used under the MOH system,[6] which did not specify any clinical presentation, but stated only that the cases in the cluster had to have a temperature of 38°C or more. Repeat consultations, defined as cases who consulted again within a 7-day period, were discarded, as the aim was to simulate outbreak detection through cases at their first presentation.

Based on analysis of this data, we set an arbitrary surveillance threshold that would not generate more than 1 false alarm in 20 days (i.e., <5% of time under surveillance), i.e., a specificity of 95%.

Model Building

Early SARS data from Tan Tock Seng Hospital (TTSH) possibly represented extended-source outbreaks,[9] where unrecognised cases of SARS in inpatients infected multiple shifts of healthcare workers over several days. To simplify the analysis, we assumed the simplest scenario that an index case of SARS was introduced into the camp, and then taken off duty after being exposed to other camp-mates for a day. We then used Monte Carlo simulations[10] to model how a consequent cluster of secondary cases might present, by taking into account 4 state variables in the presentation of each case – time in days from exposure to onset (incubation time, τ), delay from onset to presentation (δ), whether a case had a temperature of 38°C or more (ϕ), and whether a case reported sick to the SAF (σ). The 4 states were assumed to be independent of each other. Hence, for each case, 4 random numbers between 0 and 1 were drawn (p_1 to p_4), and the state variables determined as follows:

Incubation Time, τ

The incubation period distribution was taken from the Weibull function derived by Kuk and Ma[11] based on a subset of 50 SARS cases from the Singapore outbreak with well-defined exposures. Using the inverse Weibull function, the incubation time, τ, for each simulated case was then given by:

$$\tau = \alpha\,[-\ln(1-p_1)]^{1/\beta}$$

where p_1 is the random number drawn, $\alpha = 5.8$, and $\beta = 2.59$.

Delay to Presentation, δ

Figure 1 was constructed using 23 cases of probable SARS in healthcare workers who presented on 18 March 2003 and earlier, as obtained from previously unpublished data pertaining to the earlier phases of the outbreak in TTSH,[3,9,12,13] before the institution of staff fever screening measures (which might have modified the time to presentation). The cumulative frequency distribution in Figure 1 was then used to derive values of δ for each value of p_2 drawn (e.g., for $p_2 = 0.12$, $\delta = 0$; for $p_2 = 0.85$, $\delta = 3$ and so forth).

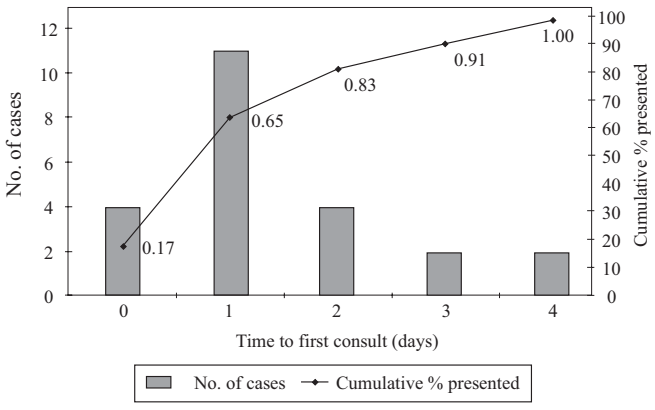

Fig. 1. Distribution of time from onset to first consult.

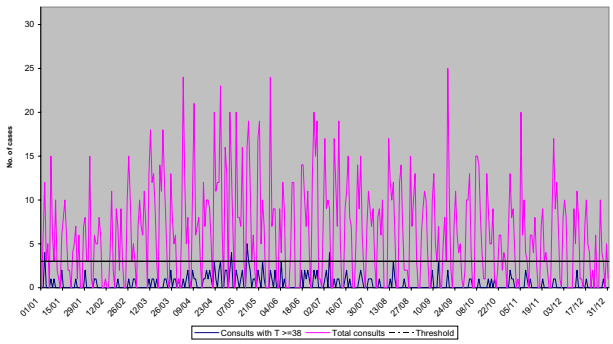

Fig. 2. Distribution of consults for 2002.

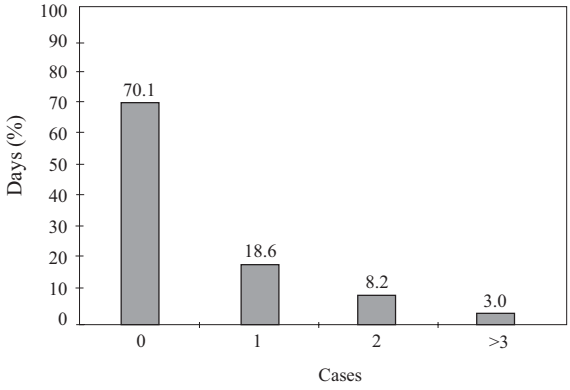

Fig. 3. Proportion of days with cases having T ≥38.

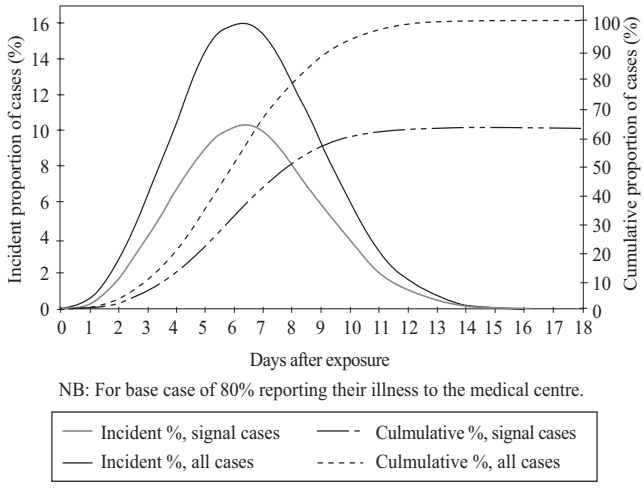

Fig. 4a. Average case presentation after exposure to SARS.

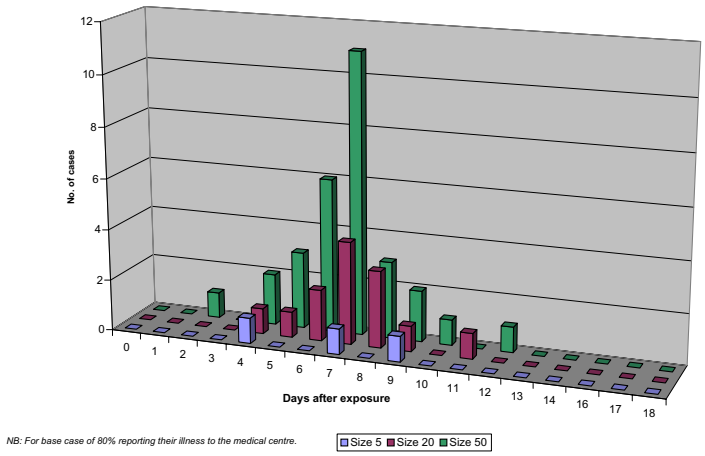

Fig. 4b. Signal cases for 3 sample outbreaks of size 5, 20 and 50.

Temperature of 38°C or more, ϕ

The best available data for this were from a study showing that only about 80% of SARS cases had T ≥38 at time of admission.[5] ϕ takes the value 1 (i.e., febrile at presentation) for values of p_3 <0.8, and 0 for values >0.8.

Reporting Sick to the SAF, σ

As not all cases would seek medical care within the SAF, we performed a sensitivity analysis for variable proportions of 60%, 80% and 100% reporting their illness to the SAF, using 80% as the base case. Hence, for the base case, s takes the value 1 (i.e., reports sickness to SAF) for values of p_4 <0.8, and 0 for values >0.8.

Only cases with both T ≥38 (ϕ = 1) and which reported sick to the SAF (σ = 1) would contribute to surveillance signals; such cases are henceforth referred to as "signal cases".

The randomly generated cases were then stringed together into outbreaks from size 5 to 50, in increments of 5. One thousand outbreaks were simulated for each outbreak size tested in the model. The simulated outbreaks were separately inserted into the background surveillance data for each of the first 355 days of 2002, simulating independent exposures occurring on these days. For example, for a simulated outbreak where exposure occurred on 1 January, a case presenting with fever after 3 days would consult on 4 January, and be summated with the surveillance data for that day. A surveillance signal would be generated if the number of signal cases, combined with background cases of febrile illness, exceeded the set threshold. Successful detection occurred where there was at least one surveillance signal from that insertion of the outbreak that fulfilled the following conditions:

- The surveillance signal had to consist of at least one outbreak case (i.e., signals arising purely from background cases did not qualify).
- The surveillance signal had to be within 8 days of the simulated exposure date of the outbreak.

The above was an arbitrarily chosen duration which would allow the peak from secondary cases to present, and

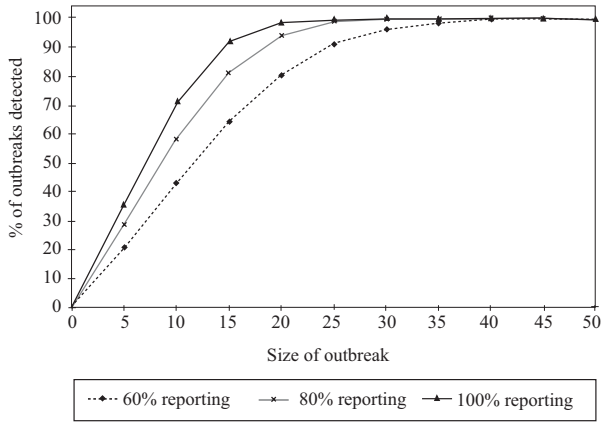

Fig. 5a. Probability of outbreak detection, incorporating delays to presentation.

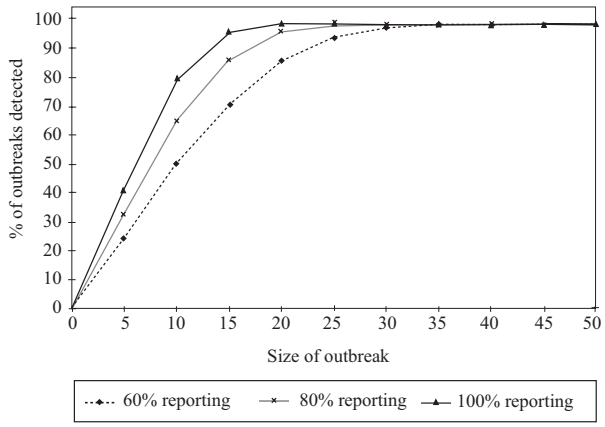

Fig. 5b. Probability of outbreak detection, ignoring delays to presentation.

which the authors felt would not too late for meaningful outbreak control. The sensitivity of the surveillance system was defined as the total number of outbreaks successfully detected divided by the 355,000 simulated outbreaks inserted (i.e., 1000 outbreaks for each of the 355 starting points for outbreak insertion).

All simulations and data processing were executed using random number and other functions in Microsoft Excel and Microsoft Access.

Results

There were 7921 consults (mean of 21.7 consults per day) for the period of observation. After discarding 315 repeat consultations, there were 2305 consults for the 3 selected syndromes. Valid temperature data were available for 2012 consults (87.2%), and further analysis focused only on these cases.

Figure 2 shows the pattern of syndromic consults with and without documented fever (T ≥38) in the background surveillance data. Documented fever was observed in 166 consults (8.3%). Figure 3 shows the proportion of days with varying numbers of consults having T ≥38. There were only 11 days (3% of all days under surveillance) with 3 or more persons having documented fever over the 365-day period. In order to obtain a specificity in excess of 95%, we chose 3 or more cases as the threshold for a surveillance signal.

Figure 4a shows the average distribution of medical consults over time following an exposure to SARS, as derived from a simulation of 50,000 randomly generated cases. The number of cases presenting reaches its maximum value between 6 and 7 days after the exposure; the peak number of cases would, on average, comprise 16% of all cases infected. Under the most likely parameters, the "signal cases" at the peak would be even less, and would comprise only about 10% of the entire outbreak size. Using sample outbreaks of size 5, 20 and 50, Figure 4b illustrates how such outbreaks might present. At size 5, the signal cases are scattered over several days. At size 20 and above, however, a distinct peak of signal cases occurs, allowing a surveillance signal to be generated.

Figure 5a gives the probability of detection for various outbreak sizes, with sensitivity estimates for 60%, 80% and 100% of soldiers reporting to their designated medical centre. If 80% report their illness to the SAF, it would take outbreak sizes of 20 or more cases to have a probability of detecting an outbreak that exceeds 90%; 100% sensitivity is only achieved at outbreak sizes of 30 and above. In addition, we repeated the analysis to see if system performance would significantly improve if we could eliminate all delays to presentation, such as through a routine of daily temperature taking for all soldiers (Fig. 5b). However, even under this optimistic assumption of no delays between onset and presentation, we were still only able to achieve a 90% success rate of detecting outbreaks for outbreak sizes of 20 and above.

Discussion

The above analysis is one of the first to attempt the use of consult data from a primary care setting for the purposes of syndromic surveillance, and to estimate possible performance for such a system. By using body temperature readings at consult, the system was able to screen out a substantial amount of background noise in primary care data. Only 8.3% of consults for the selected syndromes in our cohort had documented fever (T ≥38); in contrast, the majority of cases with SARS present with documented fever.[5]

However, in spite of this, the inclusion of documented fever alone in the case definition does not make a surveillance system based on the detection of febrile clusters sufficiently sensitive to small outbreaks of SARS. The present

assessment is that 100% detection can only be achieved with outbreak size of 30 cases or more following an exposure limited to a single day. While super-spreader events in SARS[11,14,15] could foreseeably generate such outbreak sizes, smaller outbreaks will likely be missed. Moreover, the above is an optimistic result, as we had made the simplifying assumption that the exposure would be limited to 1 day. Should the actual times of infection for secondary cases be spread over the course of several days, even larger outbreaks would be needed to confidently generate a surveillance signal.

We have analysed the weaknesses of the above system in order to understand its less than adequate performance and identify potential solutions. Firstly, the system lacks the clinical data with which to construct more specific case definitions – the addition of clinical features, or the use of some other severity index, such as repeated healthcare consults and the need for onward referral (such as for chest radiographs or admission to hospital), could reduce background noise from other conditions. In addition, the present data were analysed at the level of a medical centre, and smaller units of analysis are yet possible in the context of an army camp. Both these methods may allow lower thresholds to be set. Also, as the system is sensitive to the proportion of soldiers who present their illness to facilities outside the SAF medical centre, mechanisms for feeding such consult back data into the surveillance system will maximise the potential for creating a surveillance signal. In addition, policy measures to reduce delays in the reporting of illness will narrow the timeframe over which an epidemic presents, generating peaks that are more easily detected, although we note that the gain in performance from this alone is not enough to make the system sufficiently sensitive (Fig. 5b). Lastly, we note that at its minimum, a cluster must, by definition, include at least 2 cases over a specific time and space. One major limitation of our system is the reliance on a simple threshold of 3 cases or more per day. Methods that summate signals on adjacent days, such as CUSUM analysis,[16] may hence be useful for improving outbreak detection by a fever cluster detection algorithm. Hence, one limitation of this study was that the only surveillance algorithm assessed was a simple threshold selected on the basis observations based on the existing data, and further modelling work on other surveillance algorithms would be welcome.

The study had a few other limitations. Firstly, the time period of background surveillance data spanned only a year; this is too short a timeframe for formal assessment of any seasonal effects. However, we note that, other than for some clustering around May 2002, most of the 11 occasions where consults for $T \geq 38$ exceeded the threshold (Fig. 2) were scattered across the year, implying the lack of a clear seasonal effect. Moreover, a longer time series from the SAF PACES data (without temperature readings) showed no definite seasonal pattern.[17] As such, we decided to assume the lack of seasonal effects when setting the surveillance threshold for our model. We also made one other key assumption in our model – we assumed that, for every simulated case, the 4 state variables were independent. This assumption may be invalid, in particular, if cases that were febrile also tended to consult earlier. The model can be updated should more detailed clinical studies on the times and mode of presentation emerge. For now, however, we note that the sensitivity analysis in Figure 5b shows that removing all delays to presentation does not significantly improve the performance of the surveillance system. Hence, any correlation between time of presentation and temperature at consult is unlikely to change the conclusions of this study.

Certainly, a single case of SARS in present times will be considered an outbreak. Late recognition may lead to delayed isolation, which has been shown to have serious consequences for onward transmission.[18] There is hence a pressing public health need to identify cases as early as possible. However, several experts have pointed out the challenges in making a diagnosis of SARS based on clinical and laboratory findings alone.[19] The drive to develop early detection systems based on clusters of febrile illness is hence understandable. However, the above analysis shows that such systems are not without major limitations – the system assessed in this paper can only function with confidence for very large outbreaks. We are not alone in reporting such orders of magnitude in a syndromic surveillance publication. Reis and Mandl[20] modelled the performance of a system based in an average emergency department, and found it to require 30 cases presenting per day to achieve 100% sensitivity with an equivalent specificity. Unfortunately, detection limits of the order of those in Reis and Mandl's paper and ours are of little practical use for most emerging infectious diseases.

However, syndromic surveillance systems like the one assessed here may still be useful in 2 circumstances. Firstly, in a successful release of a bioterrorism agent, the initial number of presenting cases may be much higher; in such a situation, it is speculated that a syndromic surveillance system may provide first warning. Secondly, a retrospective analysis of historical outbreaks found significant delays between the onset of cases and the reporting of the incident. In a review of outbreak investigations, it was found that outbreak reporting was delayed for 14 to 26 days in 3 out of 6 incidents where bioterrorism was considered.[21] One purpose of syndromic surveillance may hence be to act as a safeguard to ensure timely detection in the event of multiple system failures.

Conclusions

Syndromic surveillance systems remain unvalidated in their usefulness. Our assessment of one potential system, based on clinical syndromes and documented fever at consult, shows that the system is only able to detect large outbreaks with a high degree of certainty. This limitation must be emphasized both to public health surveillance teams and policy makers, and further refinements and research are needed before such systems can be implemented with confidence.

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