Approximation of Influenza-like Illness Rates Using Sleep and Cardiorespiratory Data From a Smart Bed

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INTRODUCTION

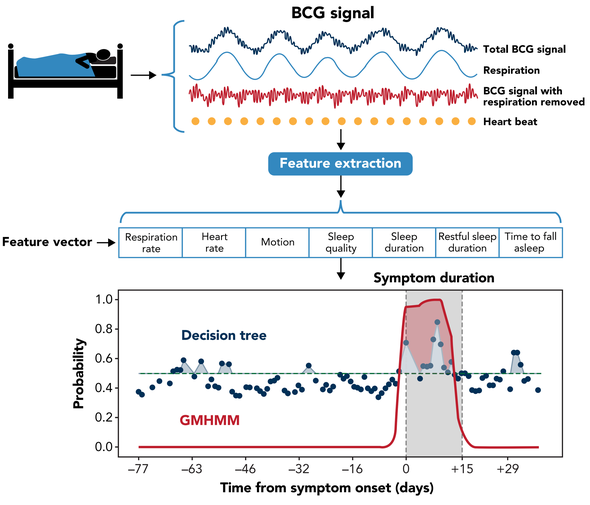
- Pathophysiologic responses to viral infections affect sleep duration, quality, and concomitant cardiorespiratory function.[1,2]
- Real-world longitudinal monitoring of sleep metrics using a smart bed could prove invaluable for infectious disease detection.
- Previously, we leveraged sleep metrics from a smart bed to build a COVID-19 symptom detection model.[3]
- An initial analysis of prepandemic data using this model indicated that this approach may generalize to detecting symptoms of other influenza-like illnesses (ILIs).[3]
- Here we investigated whether seasonal trends in ILI rates reported by the US Centers for Disease Control and Prevention (CDC) could be approximated from the aggregation of individual ILI symptom predictions from our COVID-19 symptom detection model.

METHODS

COVID-19 model development

- An independent review board-approved survey with COVID-19-specific questions was presented to opting-in Sleep Number customers from August 2020 to November 2020 in the United States.
- COVID-19 test results were reported by 3546/9370 respondents (249 positive; 3297 negative).
- Sleep duration, sleep quality, duration of restful sleep, time to fall asleep, respiration rate, heart rate, and motion level were obtained using ballistocardiography signals from the smart bed.
- Longitudinal sleep data from January 2020 to December 2020 from 122 of the positive respondents and 1603 of the negative respondents were used to develop an individual-level COVID-19 symptom-detection model that provided a probability of experiencing COVID-19 symptoms for each sleep session.
- We designed the symptom-progression model (**Figure 1**) as follows:
  - A gradient-boosted decision tree was developed using sleep-session metrics to predict the presence or absence of symptoms for each sleep session.
  - A Gaussian Mixture Hidden Markov Model (GMHMM) was built on top of the decision tree to account for the temporal dimension of the data; this predicted the onset of symptoms and duration of symptoms in days.

FIGURE 1: COVID-19 SYMPTOM-DETECTION MODEL OVERVIEW.



BCG, ballistocardiogram; GMHMM, Gaussian Mixture Hidden Markov Model.

Data analysis

- Prepandemic sleep data from January 2017 to December 2019 from 4187 responders with ≥100 sleep sessions recorded in 2017–2019 (1820 sleep sessions per night on average, 36 months total) were used to assess the ability of the COVID-19 symptom-detection model to generalize to ILI symptom-detection.
- The dataset was split into 2 equal parts for training and testing:
  - Data from the first 18 months were used to fit the CDC data.
  - Data from the second 18 months were used to calculate prediction metrics.
- Weekly rates of high-scoring sleep sessions between January 2017 and June 2018 were fitted to the weekly ILI rates as reported by the CDC using a negative binomial model. Subsequently, Pearson correlation coefficients were calculated for the predicted and reported rates between July 2018 and December 2019.
- GMHMM probability scores of experiencing ILI symptoms were obtained for each sleep session.
- Proportion of scores higher than the probability threshold (0.8) was calculated for each week.
- Reference national CDC ILI rates were obtained from FluView Interactive.[4]

ILI rate-prediction models[5]

- The **H1 (full) model** used a negative binomial regression with exposure:

$$\log y_i = b_0 + b_p p_{i-3} + b_x x_i + \log n_i, \text{ where}$$

  - y_i is the absolute ILI count for week i,
  - p_{i-3} is the 3-week lagged ILI rate,
  - x_i is the proportion of GMHMM abnormal scores (ie, that exceeded the threshold) for week i, and
  - n_i is the number of outpatient office visits for week i.
  - Coefficients b_0, b_p, and b_x were fitted using the training set.
- The **naïve model** assumed that only the proportion of GMHMM abnormal scores determined the ILI rate:

$$\log y_i = b_0 + b_x x_i + \log n_i$$

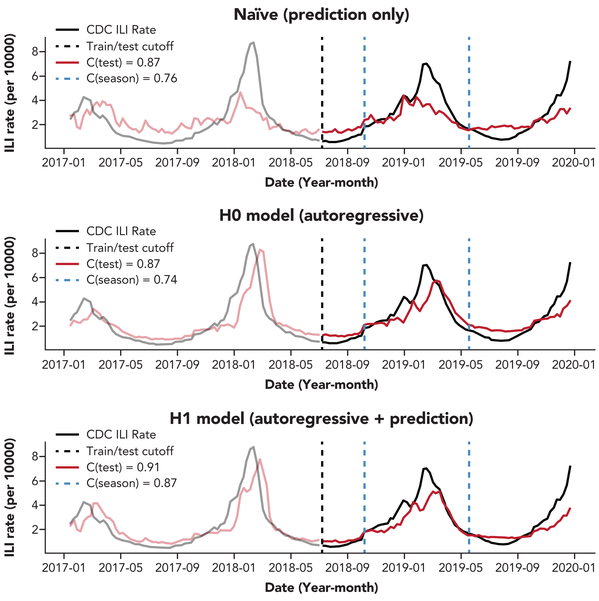
- The **H0 (null hypothesis) model** used a 3-week lagged autoregressive model, and assumed that our prediction had no effect:

$$\log y_i = b_0 + b_p p_{i-3} + \log n_i$$

RESULTS

- Correlation between the predicted and the CDC reference in the H1 model was 0.91, versus 0.87 in both the naïve model and the H0 model (**Figure 2**).
  - When restricted to the influenza season (week 40 of 2018 to week 20 of 2019), the correlation was 0.87 in the H1 model versus 0.76 in the naïve model and 0.74 in the H0 model.

FIGURE 2: CHANGE IN ILI RATE OVER TIME.



Blue dotted lines indicate the 2018–2019 influenza season.

CDC, Centers for Disease Control and Prevention; ILI, influenza-like illness.

CONCLUSIONS

- The ILI model correlated well with the reported ILI rates from the CDC in the period from January 2017 through December 2019.
- The highest correlation with the CDC results was achieved by including both lagged indicator and our model output (H1). The largest improvement in the correlation was achieved during the influenza season (+0.13 compared with the baseline model, H0, and +0.11 compared with the naïve model).
- The smart bed system is a unique source for longitudinal, ecologically valid data that can be collected unobtrusively and that may provide a method to predict and track the development of symptoms associated with respiratory illnesses, including influenza and COVID-19.

REFERENCES

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