# Longitudinal, Unobtrusive, and Ecologically Valid Sleep Metric Estimation From a Smart Bed to Predict the Pathology of COVID-19

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## INTRODUCTION

- Pathophysiologic responses to respiratory viral infection affect sleep duration and quality in addition to breathing function.
- Coronavirus disease 2019 (COVID-19) is caused by infection with the SARS-CoV-2 virus; symptoms include fever, cough, shortness of breath, fatigue, and myalgia.
  - These symptoms overlap with other respiratory diseases (influenza, severe acute respiratory syndrome, and Middle East respiratory syndrome).[1,2]
- Early detection of influenza-like symptoms is important to encourage diagnostic testing, mitigate the spread of disease, and enable early treatment.
- "Smart" and "connected" devices that monitor biosignals over extended periods of time hold promise for infectious disease monitoring.
  - They can establish baseline biometric signals and detect substantial deviations from baseline during illness.[3]
  - When used in conjunction with predictive platforms, device users could be alerted if changes consistent with COVID-19 are detected.[4]
- Sleep promotes recovery from infectious disease, whereas sleep disturbance and deprivation negatively affect immune function.[5–10]
- We leveraged longitudinal, biometric data captured in an unobtrusive, real-world manner using ballistocardiography (BCG) signals from a consumer smart bed platform to predict, at the individual level, the presence and duration of COVID-19 symptoms.

## METHODS

- From August 2020 to November 2020, an Institutional Review Board (IRB)-approved survey was presented to Sleep Number™ smart bed users who provided electronic consent to be contacted to participate in scientific research.
- Of more than 9000 smart bed users who completed the survey (a 29% response rate), 3546 reported the result of a COVID-19 test.
- After excluding participants who were not tested for COVID-19 (n = 5824), the data were further curated for quality and completeness using the criteria listed in **Table 1**.

For more information and to download this poster, please scan the QR code.

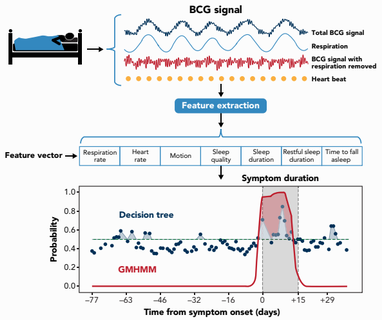
**TABLE 1. QUALITY CONTROL GUIDELINES FOR DATA TO BE USED IN THE FINAL ANALYSIS**

| Data filter | COVID-19 positive | COVID-19 negative |
|---|---|---|
| Reported dates | Start and end date of the symptomatic period | Test date |
| Consistency | Start date is before end date | Absence of dates indicating a symptomatic period |
| Data availability for the dates of interest | ≥ 3 sleep sessions during the symptomatic period | ≥ 3 sleep sessions in the time interval: test date ± 7 days |
| Data availability outside the dates of interest | ≥ 3 sleep sessions outside symptomatic period | ≥ 3 sleep sessions outside of the time interval: test date ± 7 days |

COVID-19, coronavirus disease 2019.

- Values for 7 metrics were obtained from each sleep session based on BCG signals: respiration rate, heart rate, motion level, sleep quality, sleep duration, restful sleep duration, and time to fall asleep.
- Data from January 2019 to December 2020 were included for modeling purposes.
- We designed a symptom progression model (**Figure 1**) as follows:
  1. A gradient-boosted decision tree was developed using sleep session metrics.
     - This predicted the presence or absence of symptoms for each sleep session.
  2. 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: OVERVIEW OF THE STUDY APPROACH FOR DATA COLLECTION AND MODEL DEVELOPMENT**




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

- To detect sickness while preserving temporal causality, we used a forward algorithm, which calculated the probability of a state at a certain time given the history of evidence.
- A forward-backward algorithm was used to reassess the predictions because it calculates the probability of a state conditioned on both past and future data.

## RESULTS

- The demographics and comorbidities of the study cohort are shown in **Table 2**.

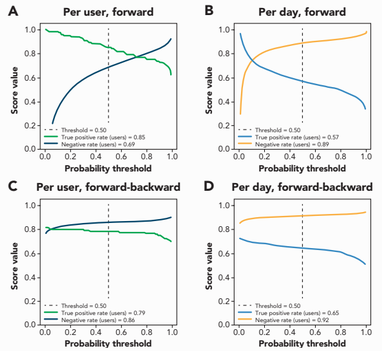
**TABLE 2. DEMOGRAPHICS AND COMORBIDITIES OF THE STUDY COHORT**

| | Cohort after quality control steps (n = 1725) | COVID-19 positive (n = 122) | COVID-19 negative (n = 1603) |
|---|---|---|---|
| Age, mean (SD) | 49.5 (13) | 45.6 (11.9) | 49.8 (13.1) |
| Men, n (%) | 820 (47.5) | 49 (40.2) | 771 (48.1) |
| BMI, mean (SD) | 30.2 (6.9) | 30.4 (7.4) | 30.2 (6.9) |
| **Comorbidities** | | | |
| Smokes, n (%) | 166 (9.6) | 8 (6.6) | 158 (9.9) |
| Asthma, n (%) | 279 (16.2) | 22 (18) | 257 (16) |
| Diabetes, n (%) | 174 (10.1) | 10 (8.2) | 164 (5) |
| CVD, n (%) | 58 (3.4) | 3 (2.5) | 55 (3.4) |

BMI, body mass index; COVID-19, coronavirus disease 2019; CVD, cardiovascular disease; SD, standard deviation.

- Our data revealed that symptom exacerbation in COVID-19–positive users (n=122) is associated with a significant increase in sleep duration, respiration rate, heart rate, restful time, and motion.
- Furthermore, COVID-19 symptom exacerbation was associated with a decrease in sleep quality, and no apparent change in the time to fall asleep.
- At the 0.5 probability threshold, the recall-per-user symptom detection rate was 85%, whereas the per-day recall was 57% (negative per-day rate 89%) (**Figure 2A**, **2B**).
- The "prediction overlap" corresponded to the mean Jaccard similarity (ratio of intersection over union) of the reported versus predicted symptomatic days.
- Factoring in a backward GMHMM pass improved most metrics at the cost of causality (**Figure 2C**, **2D**).
  - The recall-per-user rate was slightly lower because some of the predictions that were correct by chance were eliminated, which was reflected in the higher negative rate.

**FIGURE 2. MODEL PERFORMANCE USING THE FORWARD AND FORWARD-BACKWARD ALGORITHMS TO PREDICT DISEASE PROGRESSION**

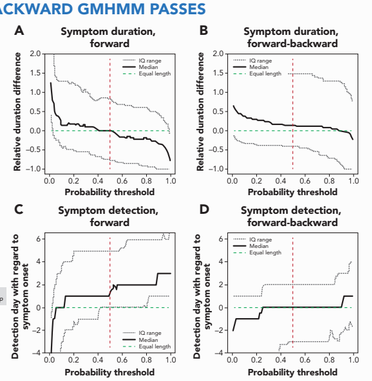



- The average duration of predicted symptoms was consistent with the duration of symptoms reported by users (**Figure 3A**, **3B**).
- Using the forward algorithm, we detected 25% of cases by day 0 and 75% of cases by day 5, with a median detection delay of 1 day (**Figure 3C**).
- Using the forward-backward algorithm, we detected 50% of cases by day 0 and 75% of cases by day 2, with a median detection delay of 0 days (**Figure 3D**).

**FIGURE 3. SYMPTOM DETECTION AND ESTIMATION OF SYMPTOM DURATION USING FORWARD AND FORWARD-BACKWARD GMHMM PASSES**

$$R_{duration} = \frac{L_{pred} - L_{rep}}{L_{rep}}$$

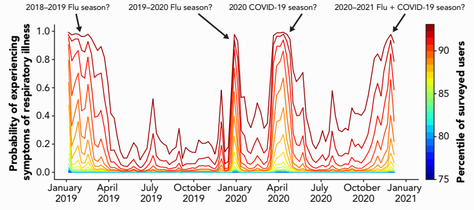
$$R_{detection} = D^{0}_{pred} - D^{0}_{rep}$$




The horizontal, green, dashed line shows same-day symptom duration (panels A, B) and same-day detection (panels C, D).
The vertical, red, dashed line shows the 0.5 severity threshold.
D0, detection day; GMHMM, Gaussian Mixture Hidden Markov Model; IQ, interquartile; L, duration; pred, predicted; rep, reported.

- The distribution of the probabilities for experiencing symptoms predicted by our model was plotted for all surveyed users (N = 9370; **Figure 4**).
- Some probability peaks predate the COVID-19 pandemic, suggesting that our model system can detect respiratory illnesses that are not caused by SARS-CoV-2.

**FIGURE 4. PROBABILITIES OF RESPIRATORY ILLNESS PREDICTED BY OUR MODEL SYSTEM FOR ALL SURVEYED USERS.**




The 75th to 95th percentiles are shown in a gradient from blue to red. The captions for the flu/COVID-19 seasons represent our conjectures. COVID-19, coronavirus disease 2019.

## CONCLUSIONS

- To our knowledge, this is the first study to use longitudinal data collected unobtrusively under real-world conditions during sleep by a smart bed platform to monitor symptoms of COVID-19 and to predict the incidence of confirmed COVID-19.
- The sleep metrics measured with this platform are a unique source of long-term health data that can be used to predict and track the development of symptoms associated with respiratory disease.

## REFERENCES

**1.** Larsen JR et al. *Front Public Health*. 2020;8:473; **2.** Hu T et al. *Peer J*. 2020;8:e9725; **3.** Zhu G et al. *Discrete Dyn Nat Soc*. 2020;1-8; **4.** Seshadri DR et al. *Front Digit Health*. 2020;2:8; **5.** Besedovsky L et al. *Physiol Rev*. 2019;99(3):1325-1380; **6.** Vgontzas AN et al. *J Clin Endocrinol Metab*. 1999;84:2603-2607; **7.** Taylor DJ et al. *Behav Sleep Med*. 2017;15(4):270-287; **8.** Lange T et al. *J Immunol*. 2011;187:283-290; **9.** Patel SR et al. *Sleep*. 2012;35:97-101; **10.** Cohen S et al. *Arch Intern Med*. 2009;169:62-67.

## ACKNOWLEDGMENTS

We thank Dr. Eve Van Cauter, PhD, University of Chicago School of Medicine (Chicago, IL), for her helpful feedback on this poster. Medical writing support for this manuscript was provided by Sandra Page, PhD, of Oxford PharmaGenesis, Inc, Newtown, PA, USA, and was funded by Sleep Number Corporation.

## DISCLOSURES

**DG:** Employee of GlobalLogic. GlobalLogic is a consultant under contract with Sleep Number Corporation; **KM:** Employee of Sleep Number Corporation at the time of study; **VKS:** Has consulted for Bayer, Jazz Pharmaceuticals, Baker Tilly, and Respicardia, and is on the Sleep Number Scientific Advisory Board; **DS**, **FM**, **FS**, **GGM**, **JC**, **SD:** Employees of Sleep Number Corporation.

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***Poster presented at: SLEEP 2021, June 10–13, 2021. Virtual meeting: https://sleepmeeting.org***