



# Non-contact thermography-based respiratory rate monitoring in a post-anesthetic care unit

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Received: 8 June 2020 / Accepted: 18 September 2020 / Published online: 25 September 2020  
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## Abstract

In patients at high risk of respiratory complications, pulse oximetry may not adequately detect hypoventilation events. Previous studies have proposed using thermography, which relies on infrared imaging, to measure respiratory rate (RR). These systems lack support from real-world feasibility testing for widespread acceptance. This study enrolled 101 spontaneously ventilating patients in a post-anesthesia recovery unit. Patients were placed in a 45° reclined position while undergoing pulse oximetry and bioimpedance-based RR monitoring. A thermography camera was placed approximately 1 m from the patient and pointed at the patient's face, recording continuously at 30 frames per second for 2 min. Simultaneously, RR was manually recorded. Offline imaging analysis identified the nares as a region of interest and then quantified nasal temperature changes frame by frame to estimate RR. The manually calculated RR was compared with both bioimpedance and thermographic estimates. The Pearson correlation coefficient between direct measurement and bioimpedance was 0.69 ( $R^2 = 0.48$ ), and that between direct measurement and thermography was 0.95 ( $R^2 = 0.90$ ). Limits of agreement analysis revealed a bias of 1.3 and limits of agreement of 10.8 (95% confidence interval 9.07 to 12.5) and  $-8.13$  ( $-6.41$  to  $-9.84$ ) between direct measurements and bioimpedance, and a bias of  $-0.139$  and limits of agreement of 2.65 (2.14 to 3.15) and  $-2.92$  ( $-2.41$  to 3.42) between direct measurements and thermography. Thermography allowed tracking of the manually measured RR in the post-anesthesia recovery unit without requiring patient contact. Additional work is required for image acquisition automation and nostril identification.

**Keywords** Thermography · Respiratory rate · Patient monitoring · Bioimpedance

## 1 Introduction

Multiple components of general anesthesia affect respiratory function, including neuromuscular blockade [1], the use of volatile anesthetic agents [2, 3], and opioids [4]. Respiratory compromise is a major cause of morbidity in the post-anesthesia care unit (PACU) [5, 6], and prevention requires early detection of critical respiratory events for prompt treatment;

it also requires risk-stratification to guide appropriate dispositions after the patient leaves the PACU (e.g., intensive care unit versus step-down). Bioimpedance is the current standard technique for measuring respiratory rate (RR) in clinical settings. It applies a voltage across the thorax and measures the current (and hence resistance) that passes through the thorax. Because air, muscle, bone, and blood all have different resistances, changes in the chest cavity dimensions affect changes in measured resistance, and these changes are used to estimate the RR. Bioimpedance-based measurements have several disadvantages: they do not actually measure gas exchange, they require patient contact, and they can be affected by electrode position-related errors, among other causes of error.

Previous authors have postulated that thermography may be used to measure RR in lieu of bioimpedance [7]. Thermographic RR measurements rely on the concept of temperature change in the air occupying breathing pathways. With each inspiration and expiration, gas at room air

**Electronic supplementary material** The online version of this article (<https://doi.org/10.1007/s10877-020-00595-8>) contains supplementary material, which is available to authorized users.

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temperature cools the nose and mouth to room temperature (or close to it), and warm air at body temperature heats the nose and mouth. Thermographic imaging devices capture these cyclical oscillations in temperature. Thermography has two advantages over bioimpedance-based measurements: it does not require patient contact, and it relies on actual gas exchange instead of chest wall movements. This study determined the accuracy of thermographic estimates of RR in a population of post-surgical patients, using direct visualization as the gold standard.

## 2 Methods

### 2.1 Background

This observational study was conducted in accordance with the Declaration of Helsinki, and the study protocol was approved by the Ethics Committee of the University of Virginia, VA (IRB No. 21353). It was registered on ClinicalTrials.gov (NCT04005911). Data were collected in the PACU at the University of Virginia Hospital from April 18 to May 14, 2019. Inclusion criteria were the ability to give consent, age over 18 years, and a planned postoperative stay in the PACU. We excluded patients using oxygen masks since thermographic detection through a mask might be inadequate. Investigators obtained verbal consent from spontaneously ventilating patients who were using nasal cannulas or no supplemental oxygen and who were alert enough to understand the risks and benefits of the study. One hundred seven patients receiving general anesthesia for non-emergent surgery were enrolled in this study.

### 2.2 Data acquisition

Investigators observed post-surgical patients monitored with a GE Healthcare patient monitor (Chicago, IL, USA) for continuous monitoring of vital signs in the PACU, as per University of Virginia institutional protocol. A FLIR T450sc (FLIR Systems, Sweden) infrared thermography (IRT) camera was positioned on a stand approximately 1 m from the patient's face and directed towards the face (Fig. 1). A 2-min IRT video (temperature scale is adjusted between 28.2 and 38.2 °C) was recorded while the investigator manually recorded the RR displayed on the GE monitor and also measured the RR by direct visualization using over 1 min as the golden standard.

### 2.3 Data processing

Our approach was based on previous attempts to measure RR thermographically in rodents [8] and healthy volunteers [9]. Based on the description by Pereira et al. [10], we developed



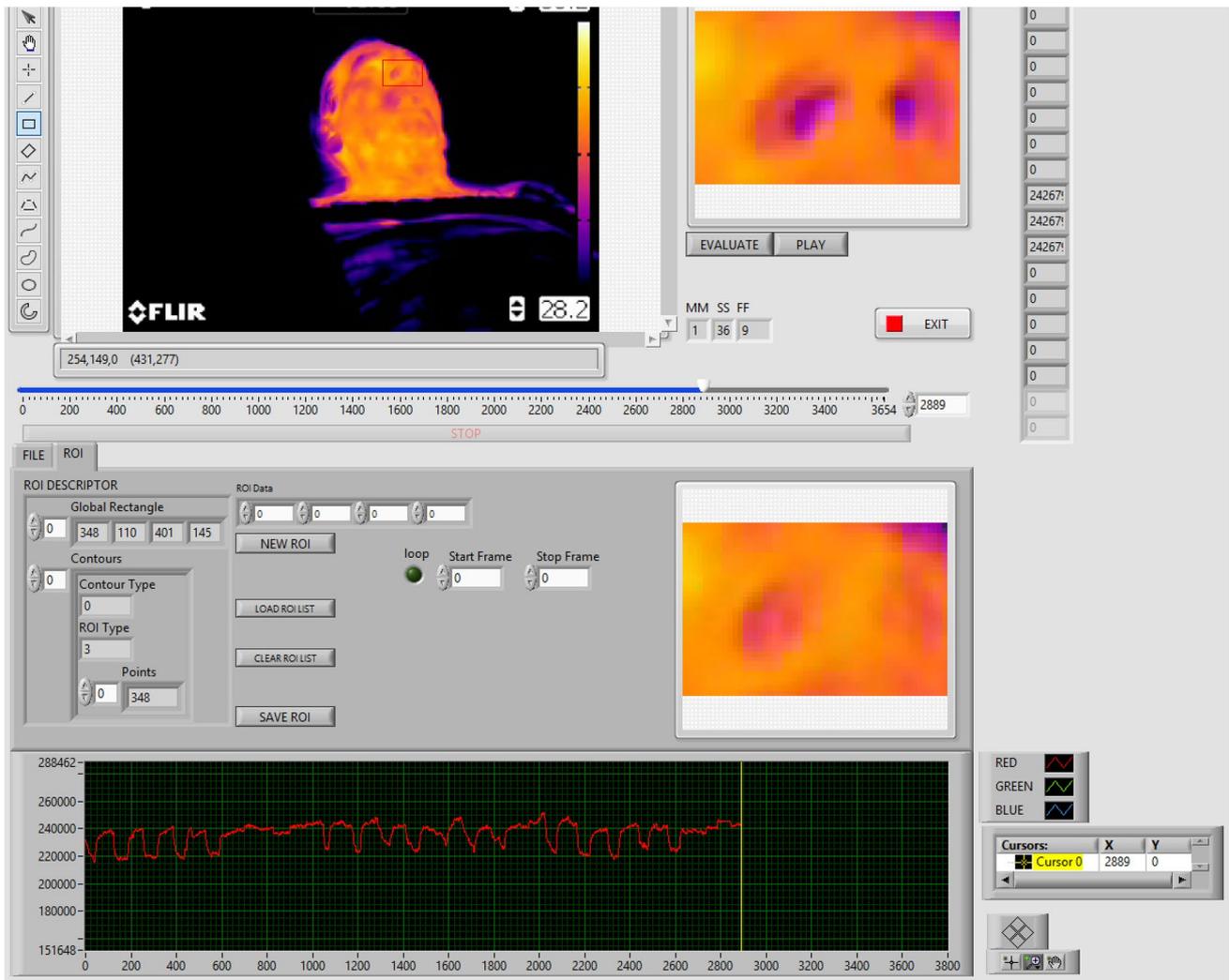
**Fig. 1** Representative picture of the thermal camera setting in the post-anesthetic care unit. The patients were closely monitored and placed in a 45° reclined position. All patients laid in the bed with an elevated upper body wearing hospital clothing and no jewelry. All patients were alert after their surgical procedures. The infrared camera was mounted on a tripod, which was positioned at the foot of the bed

a temperature change algorithm and implemented it in LabVIEW vision tools (Ver. 2018, National Instruments, Austin TX, USA). The collected data were analyzed offline, using a standardized protocol that consisted of the following steps (Fig. 2):

- 1 Manual identification of the nose.
- 2 Manual creation of a “region of interest” around the nose.
- 3 Playback of the video with extraction of the temperature in the region of interest.
- 4 Calculation of the oscillation rate of the temperature waveform. This formed the estimate of the RR (see Video, Supplemental Digital Content 1, which demonstrates a representative scene of the actual application of thermographic respiratory measurement).

### 2.4 Statistical considerations

Because of the pilot nature of this study and the fact that there are no previously published confidence intervals (CIs) around limits of agreement plots to compare thermographic RR measurement with a gold standard (direct observation), we did not conduct a power analysis and instead elected to collect data on 100 patients, which is a sample size that is somewhat larger than previous studies. Continuous variables are described as mean  $\pm$  standard deviation (SD) and categorical variables as frequencies (%), as appropriate. Student's t test, the Mann–Whitney U test, the chi-square test, or Fisher's exact test were used for



**Fig. 2** Representative picture of in-house respiratory monitoring software written in LabVIEW (National Instruments, Austin, TX, USA). Note that a transient respiratory pause (16 s) was successfully detected by this toolkit

between-group comparisons, as appropriate. We analyzed the performance of both bioimpedance-derived and thermography-derived RR compared with direct observation using correlation and limits of agreement analyses, as has been previously recommended [11]. P values < 0.05 were considered statistically significant. Statistical analyses were conducted using R software, version 3.6.2 (R Foundation for Statistical Computing, Vienna, Austria) and SPSS Statistics for Windows, version 22 (IBM Corp., Armonk, NY, USA).

### 3 Results

In total, 107 patients (42 men and 59 women) consented to participate in this study. Data from six patients could not be analyzed and were excluded, either because the ROI (nostrils) was not visible, excessive patient movement, or

interference with the video footage by the PACU care team, all of which interfered with data analysis. The mean age of the study sample was 58.5 years (SD 15.8) (Table 1).

The Pearson correlation coefficient between direct measurement of RR and bioimpedance-based measurements was 0.69 ( $R^2 = 0.48$ ). The Pearson correlation coefficient between direct measurement of RR and thermography-based measurements was 0.95 ( $R^2 = 0.90$ , Fig. 3). Limits of agreement analysis revealed a bias of 1.3 and limits of agreement of 10.8 (95% CI 9.07 to 12.5) and  $-8.13$  (95% CI  $-6.41$  to  $-9.84$ ) between direct measurements of RR and bioimpedance-based measurements. Limits of agreement analysis revealed a bias of  $-0.139$  and limits of agreement of 2.65 (95% CI 2.14 to 3.15) and  $-2.92$  (95% CI  $-2.41$  to 3.42) between direct measurements of RR and thermographic estimates of RR (Fig. 4). There were no difficulties in obtaining data from patients with mustaches or nasal prongs. The

**Table 1** Patient demographic and clinical data

Age (years)	58.5 ± 15.8
Sex (male, female)	42 (41.6%) /59 (58.4%)
Operation type	
General surgery	35 (34.7%)
Orthopedic/neurosurgery	30 (29.7%)
Urologic/gynecologic surgery	16 (15.8%)
Dental/Head and neck/Plastic surgery	10 (9.9%)
Other	10 (9.9%)
Vital signs	
Heart rate (bpm)	77.6 ± 14.1
Systolic blood pressure (mmHg)	125.7 ± 21.1
Diastolic blood pressure (mmHg)	66.2 ± 11.1
SpO <sub>2</sub> (%)	97.3 ± 10.5
Mustache	17 (16.8%)
Nasal prong	35 (34.7%)

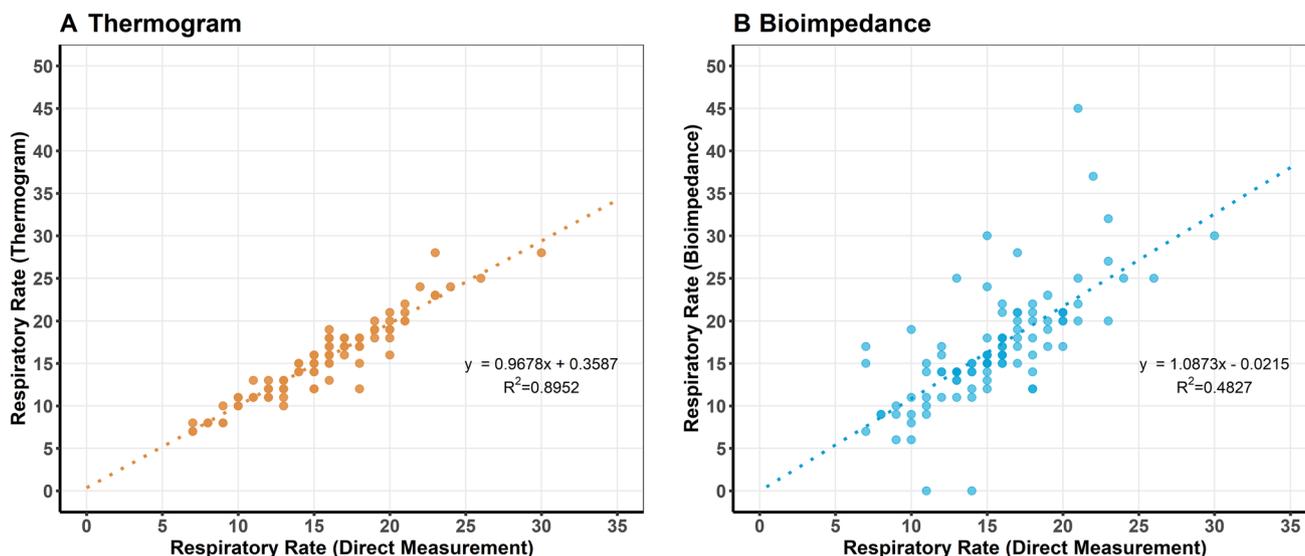
Data are presented as mean ± standard deviation or number (percentage, %)

demographic characteristics of patients with mustaches are shown in Supplementary Table 1, and those of patients with nasal prongs are shown in Supplementary Table 2. Pearson correlation data are summarized in Supplementary Fig. 1. The correlation between direct measurement of RR and thermography-based measurements was weaker among patients with mustaches ( $R^2 = 0.61$  vs.  $R^2 = 0.90$ ) than among those without mustaches, but it was stronger than the correlation between direct RR measurements and bioimpedance-based measurements.

## 4 Discussion

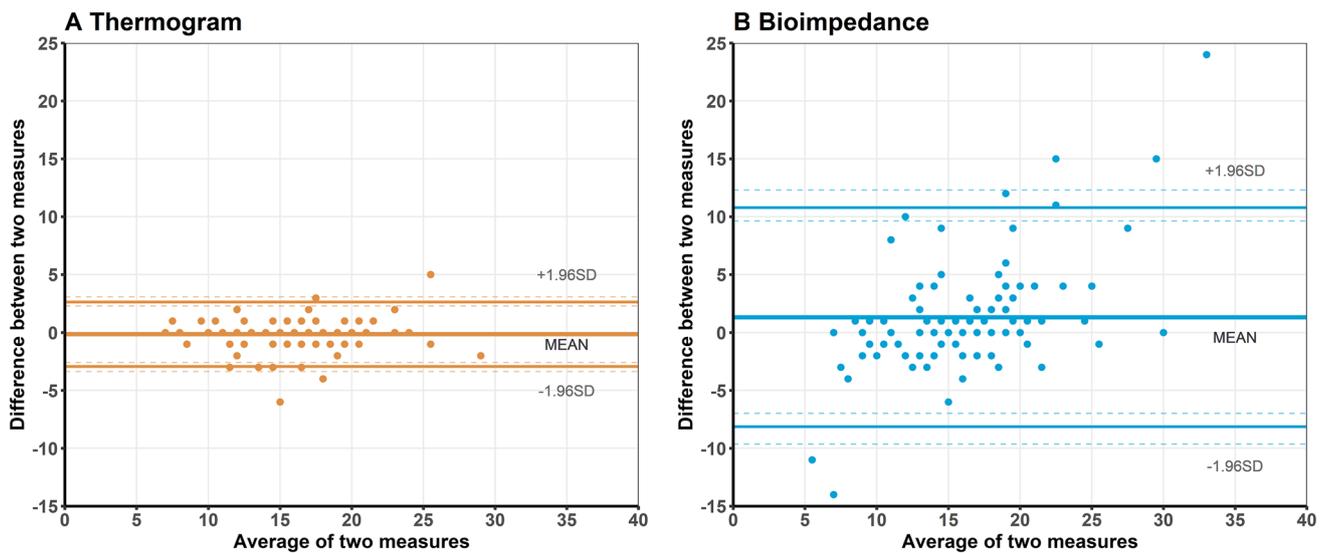
The results of this pilot study suggest that thermography has the potential to accurately measure RR in post-surgical patients. The accuracy is comparable to direct RR measurements, and thermography may be superior to bioimpedance-based measurements. There have been increasing demands for contactless, unobtrusive, feasible, and reliable techniques for monitoring patient respiration. Infrared thermography has emerged as a promising monitoring tool in various medical settings, such as fever screening [12], monitoring of thermoregulation in neonates [13], and in the PACU but only in small numbers ( $n = 28$ ) [14]. The RR measurement algorithm using thermography is based on temperature fluctuations at the region of interest (around the nostrils) during the respiratory cycle. Current study has merits in the testing the feasibility of thermography technique to applicate in the real PACU setting.

The thermographic technique has several disadvantages. It requires sophisticated hardware and software and requires an unobstructed view of the face. Accurate measurement in the setting of significant patient movement as well as with facemasks or non-invasive positive pressure devices who are higher risk of hypoxia, may not be possible. Unfortunately, in this study, some of the thermal videos (6/107, 5.6%) were excluded from the analysis for various reasons, such as patient movement or obscured nostril visualization. Differences in accuracy between “mouth breathers” and “nose breathers” remain to be elucidated. Furthermore, additional techniques for enhancing RR determination in patients with



**Fig. 3** Correlation between respiratory rate with **a** direct measurement vs. thermography ( $R^2 = 0.895$ ), and with **b** direct measurement vs. bioimpedance ( $R^2 = 0.483$ ). Note that for two cases, thoracic

impedance outputs were labeled as “apneic” while the actual measurement were 11 and 14 breaths per minute, respectively



**Fig. 4** Bland–Altman plots comparing the respiratory rates obtained with direct measurement and the corresponding respiratory rates measured with **a** the infrared thermography and **b** thoracic bioimpedance. The Y axis represents the difference between two measure-

ments, and the X axis represents the mean between two measurements. Thermography vs. direct measurement: Bias 0.1, Precision  $-2.7$  to  $2.9$ . Bioimpedance vs. direct measurement: Bias  $-1.3$ , precision  $-11.0$  to  $8.3$

obstacles (such as mustaches or nasal prongs) to detecting the region of interest should be discussed.

It is important to point out that our analysis relied on the manual identification of important facial structures (nares) and that analyses were performed offline and not in real time. However, other authors have demonstrated that automated identification and classification of facial structures is possible [7, 15], opening up the possibility of continuous, automated, and accurate RR monitoring in patients at risk of respiratory depression (including but not limited to post-surgical patients) without requiring patient contact. Autonomic detection can be achieved using Harr feature-based cascade classifiers, which are already trained to detect facial structures in visual images. In brief, the image is learned as the sums of black and subtraction white pixels (Harr features). Then, instead of evaluating entire pixels, the prevalences of certain critical features are first investigated to focus on the feature of interest. Selected features are grouped and evaluated in a staged fashion, with features discarded at any failed stage. This method allows for faster and more effective detection of the object of interest, but it is trained with visual image, not thermal images [10, 16]. Therefore, the classifier must be trained again using current data. A recent study [17] showed that adding automated thermal detection algorithms to contact methods improved RR detection compared with the contact method alone. However, the feasibility of the automated thermal model alone was not clarified.

Despite these shortcomings, thermography-based RR monitoring has great potential. First, by measuring

temperature changes due to airflow, thermographic changes are dependent on the cyclic ventilation that occurs during respiration. Second, thermography requires no patient contact, no disposables, and may be capable of measuring groups of patients with one image set. Third, thermographic respiratory monitoring may have uses outside the realm of perioperative care—potential uses include obstructive sleep apnea in adults [15], detection of apnea in infants [10], use in extubated but critically ill patients [18], mass casualty triage, and even veterinary uses. Additionally, our protocol did not rely on the ability of the camera to accurately measure the absolute temperature. The main factors affecting the performance of our protocol were the thermal sensitivity of the camera and the resolution of the focal plane array [10]. A future aim might be to integrate a motion artifact detection algorithm capable of automatic motion analysis in the thermal videos. This technique is also ideal for COVID-19 screening or long-term patient monitoring purposes.

An unanticipated finding of this study was the questionable accuracy of the bioimpedance-based RR measurements in the PACU compared with direct observation by a physician. Analysis of Figs. 3 and 4 reveals nine subjects in whom the bioimpedance-based estimate of RR effectively doubled the RR (e.g., impedance-based RR was 20, and direct measurement was 10). In a PACU environment, under direct observation by a critical care nurse, this may not be problematic, but in a ward setting with 1:6 supervision, such overestimations could be critical.

While it is clearly not yet ready for clinical use, thermography deserves serious investigation as an alternative

to bioimpedance for measuring RR in a variety of patient populations. Surely to be dismissed as inferior and niche, thermography shares several features of other “disruptive” technologies that have eventually come to replace their predecessors [19]. In the field of anesthesiology and critical care medicine, there have been many trials to estimate various kinds of vital signs using non-invasive measurement techniques, such as electrocardiography [20], pulse transit time [21], and phonocardiography [22–25]. Although we acknowledged that these techniques are still under development, we believe that all of these studies, including the present study, will improve patient safety and well-being in the near future.

Our study was among the largest studies to compare thermography to both bioimpedance and direct measurement of RR, and the findings suggest that thermography may potentially be used to estimate RR in a variety of settings without the need for any direct patient contact. The capacity of this technique to integrate an automatic analysis algorithm and to detect motion artifacts should be explored.

**Acknowledgements** We are especially thankful to the nurses in our post-anesthetic care unit who helped us identify willing participants for this study and, more importantly, allowed us to interfere with their workflow to collect these important data.

**Author contributions** Contribution: HMK helped statistical analysis and draft the manuscript. Attestation: HMK has seen the original study data, reviewed the analysis of the data, and approved the final manuscript, and this author is the author responsible for archiving the study files. Contribution: KI helped conduct the study, develop analysis software using Matlab and Labview code, analyze the data, and draft the manuscript. Attestation: KI has seen the original study data, reviewed the analysis of the data, and approved the final manuscript. Contribution: SHK helped design the study, collect the data, conduct the study, analyze the data, and draft the manuscript. Attestation: SHK has seen the original study data, reviewed the analysis of the data, and approved the final manuscript, and this author is the author responsible for archiving the study files. Contribution: RHT supervised and designed the study, helped conduct the study, collect the data, analyze the data, and draft the manuscript. Attestation: RHT has seen the original study data, reviewed the analysis of the data, and approved the final manuscript.

**Funding** This research was supported by a grant of the Korea Health Technology R&D Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (Grant No. HI18C2383 and HI18C0022).

## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** Ethical approval for this study (IRB No. 21353) was provided by the Ethics Committee of the University of Virginia, VA, USA.

**Informed consent** Informed consent was obtained from all individual participants included in the study.

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