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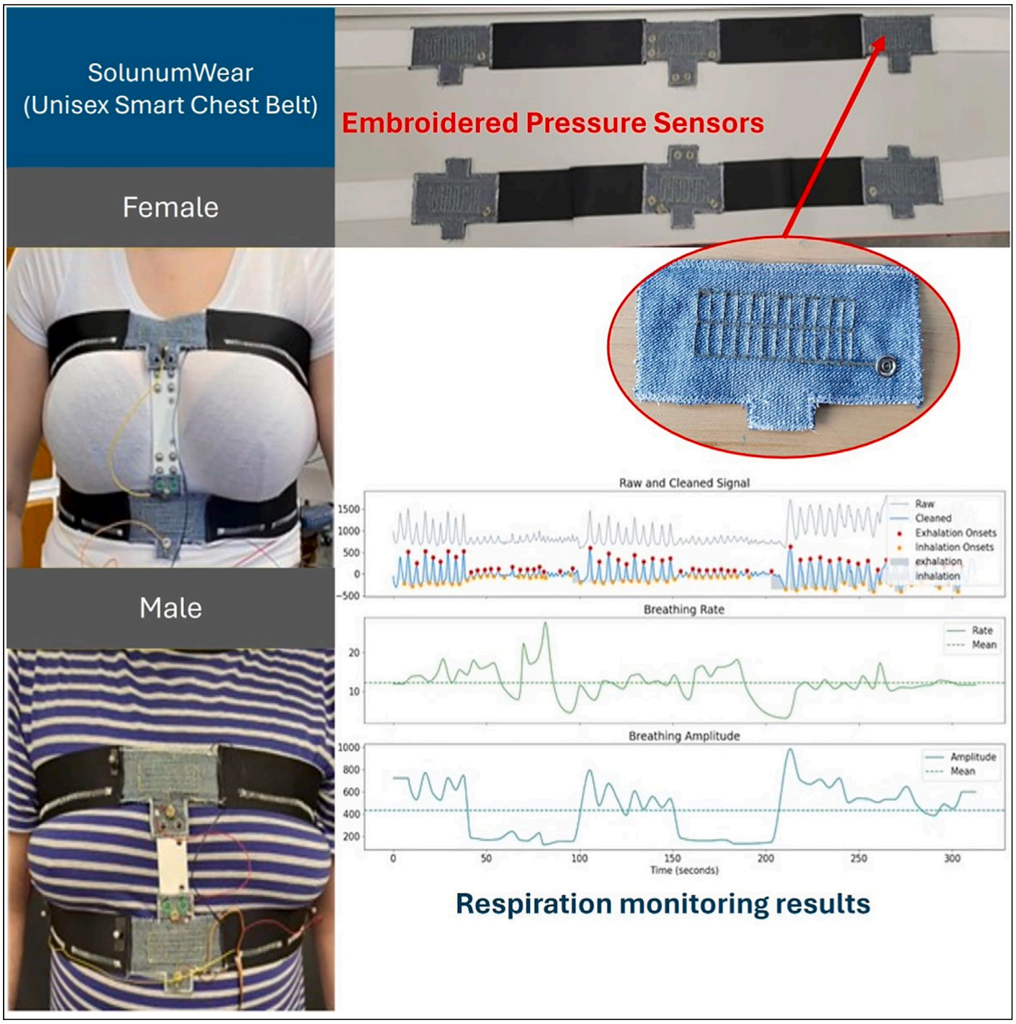

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Highlights

Smart chest belt enables respiration monitoring from chest via embroidered sensors

Custom edge device for wireless data collection highlights advances in wearables

We demonstrate high agreement compared to the gold-standard OptiTrack system

Assessing system performance in various conditions shows monitor versatility

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SolunumWear: A smart textile system for dynamic respiration monitoring across various postures

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SUMMARY

We introduce SolunumWear, a multi-sensory e-textile system designed for respiration in daily life settings, addressing the gap in continuous, real-world respiration event monitoring. Leveraging a textile pressure sensor belt to capture chest movements and a wireless data acquisition system, SolunumWear offers a promising solution for both medical and wellness applications. The system's efficacy was evaluated through a human study involving 10 healthy adults (six female and four male) across various breathing rates and postures, demonstrating a strong correlation (R value = 0.836) with the gold-standard system. The study highlights the system's computational and communication efficiencies, with latencies of approximately 4.84 s and 2.13 ms, respectively. These findings highlight the efficacy of SolunumWear as a wireless, wearable technology for respiration monitoring in daily settings. This research contributes to the expanding body of knowledge on smart textile-based health monitoring technologies, demonstrating its potential to provide reliable respiratory data in real-world environments.

INTRODUCTION

Monitoring physiological parameters such as heart rate, blood oxygen level, and respiration has seen increasing adoption, particularly since the COVID-19 pandemic. Among these parameters, respiration monitoring is under-recognized despite the fact that it could be used to evaluate various health conditions such as asthma, apnea, bronchitis, emphysema, etc.[1] Respiration can also be an important indicator of various complications affecting the critical systems such as nervous system, excretory system, and cardiovascular system.[2,3] Monitoring respiration is useful in diagnosing various diseases as well as monitoring the effects of the treatment/interventions on the patients. Reports indicate that respiration can be linked to emotions such as happiness, surprise, sadness, anger, stress, and fear.[4–7] This link between respiration and human emotions can be useful in preventing mental illness and enhancing the mental well-being of individuals.[8] Also, human emotion recognition can be useful in investigating consumer needs,[9] driver safety,[7] and virtual reality-based clinical interventions.[10–13] Respiration is also widely used in athletic training and performance improvement.[14] Monitoring respiration parameters of preterm babies (often kept in the neonatal ICUs) also play an important role in monitoring the health of those preterm babies.[15]

In this research paper, we present SolunumWear, a smart respiration monitoring system designed with electronic textile (e-textile) sensors. The system comprises an in-house developed chest belt integrated with pressure sensors and wireless infrastructure consisting of a wearable data acquisition system and a telemonitoring communication system. We conducted experiments to evaluate the performance and accuracy of the proposed respiration monitoring system compared to optical tracking system under different postural conditions. Our findings demonstrate that SolunumWear can be a reliable respiration monitoring solution for in-home, clinical, and research settings.

This paper makes the following scientific contributions in the areas of wearable systems.

- Smart textile pressure sensor design: The creation of a smart textile pressure sensor using an industrial embroidery machine represents a significant technical advancement in wearable systems. This approach enhances precision, accuracy, and reliability in detecting and monitoring chest movements. By integrating conductive materials and piezoresistive fabric (such as Velostat) through precision embroidery, the sensor's responsiveness to pressure changes caused by breathing is improved.
- Unisex chest belt: The development of a unisex chest belt that can accurately monitor respiration rates across different genders is a vital contribution. This belt is designed to accommodate anatomical differences between males and females without compromising the sensor's effectiveness. The evaluation on both genders ensures that the device is versatile and adaptable, making it suitable for widespread clinical and personal use.

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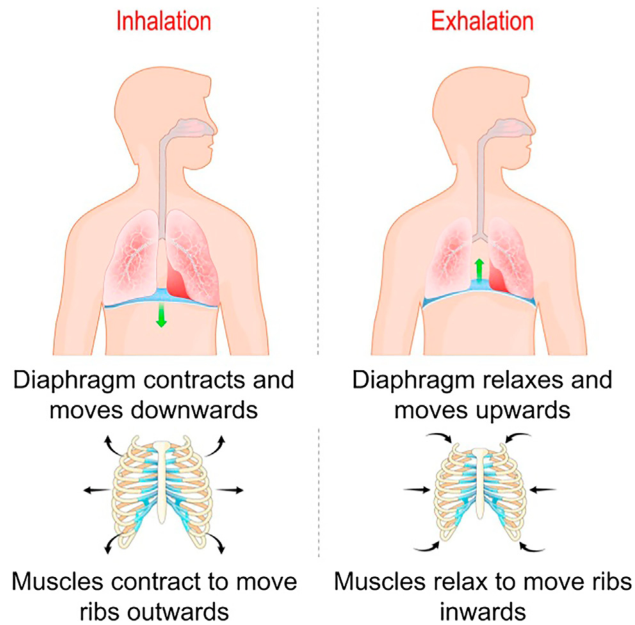

Figure 1. Anatomy of respiration mechanism

- Custom edge computing device: The design and implementation of a custom edge computing device for wireless data collection and processing highlight significant strides in wearable technology. This device facilitates real-time analysis and processing of sensor data directly from the wearable, reducing latency and dependency on external processing resources.
- Comparison with gold-standard systems: The rigorous evaluation of SolunumWear against the OptiTrack system, a gold-standard in movement tracking, provides evidence of the system's reliability and validity by demonstrating strong correlation in the sensing of breathing changes.
- Evaluation across breathing rates and postures: The comprehensive assessment of the system's performance across various breathing rates and postures (standing, sitting, and bending) addresses a critical aspect of wearable health monitors—versatility in different physical conditions. This evaluation helps in understanding how posture affects respiratory measurements and ensures that the device remains accurate across a range of everyday activities.

Background and state-of-the-art

Respiration is an important process essential for generating energy in living organisms such as humans which involves inhaling oxygen and exhaling carbon dioxide. Lungs play a key role within the respiration system and are made of tissues that work together to move fresh air into the body and remove waste gases outside. During the mechanical process of respiration, the diaphragm and intercostal muscles expand and contract. This results in expansion and contraction of the chest and or abdominal area (Figure 1).

Assessment of respiratory patterns helps the relevant clinicians understand the patient's current physiologic status. For example, during annual check-ups, physicians perform auscultation by listening to the lung sounds using a stethoscope. Thus, they examine the respiratory system (breath sounds), cardiovascular system (heart sounds and vascular bruits), and gastrointestinal system (bowel sounds).[16] Unusual or out-of-sync breathing patterns may indicate the presence of an underlying injury. Detecting these abnormal respiratory patterns early can assist healthcare professionals in taking timely action to prevent the patient's condition from worsening.[17]

There are several methods to measure the respiration-related events as shown in Figure 2. These methods can be mainly divided into two major categories, namely contact-based and non-contact-based methods. Contact-based methods involve acoustic-based methods,[18–20] airflow-based methods,[21–24] chest/abdominal movement detection,[25–28] oximetry probe (SpO2) based method,[29,30] and electrocardiogram (ECG)-based methods.[31–35] Non-contact-based methods involve radar-based respiration rate monitoring,[36–38] optical-based respiration rate monitoring,[39–42] thermal sensors, and thermal imaging-based monitoring.[43,44] Non-contact methods offer the opportunity for monitoring the user's respiration events without hindering their movements. However, these non-contact methods are limited to lab-based setup. Besides, it raises concerns related to patient safety, electromagnetic interference with medical equipment, etc. On the other hand, contact-based methods are more reliable and can be used in daily life setups.

In the past, researchers have used microphones to measure respiratory sound by placing the microphone close to the respiratory airways to measure the respiration related events.[20] Reports show that such a technique was used to detect apnea in infants.[20] The respiration can also be monitored through temperature sensing of the exhaled air, as the exhaled air will be warmer, humid, and contains more CO_2 concentration. Nasal thermistor was another method to monitor the respiration events.[23] Strain gauges were also explored to measure the expansion

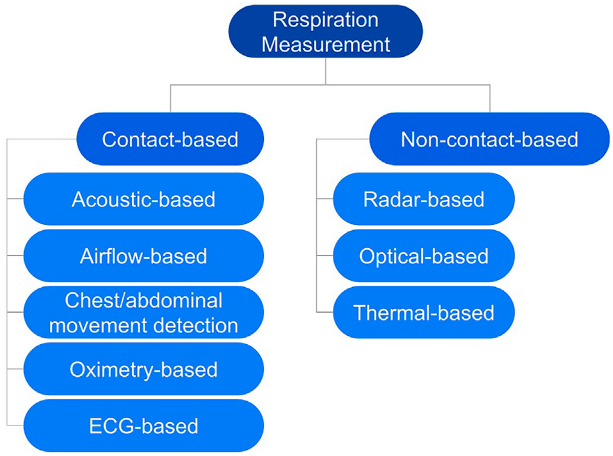

Figure 2. Respiration measurement methods

and contraction of the chest.[25] The changes in the thoracic and abdominal circumferences were monitored by placing a strain gauge around the participant's chest. Further, studies have shown that respiration can be monitored using a photoplethysmogram.[30,45–47] Respiration information was found coupled with the photoplethysmogram information and by investigating the magnitude and frequency information, researchers have extracted respiration information from photoplethysmogram. Researchers also explored ECG-derived respiration rate (EDR). EDR works on the principle that the respiratory actions create a small change in the relative position of the heart and the electrodes. Researchers have shown that respiratory information can be extracted from the ECG signal.[31–34,48] Tarassenko et al. also investigated different methods such as EDR and photoplethysmogram to record respiration information and observed the limitation of these methods.[35]

The current landscape of contact-based methods for respiratory monitoring involves a variety of sensors, each designed to capture specific types of respiratory events. Commonly used sensors include strain gauges, respiratory inductance plethysmography, and piezoelectric belts,

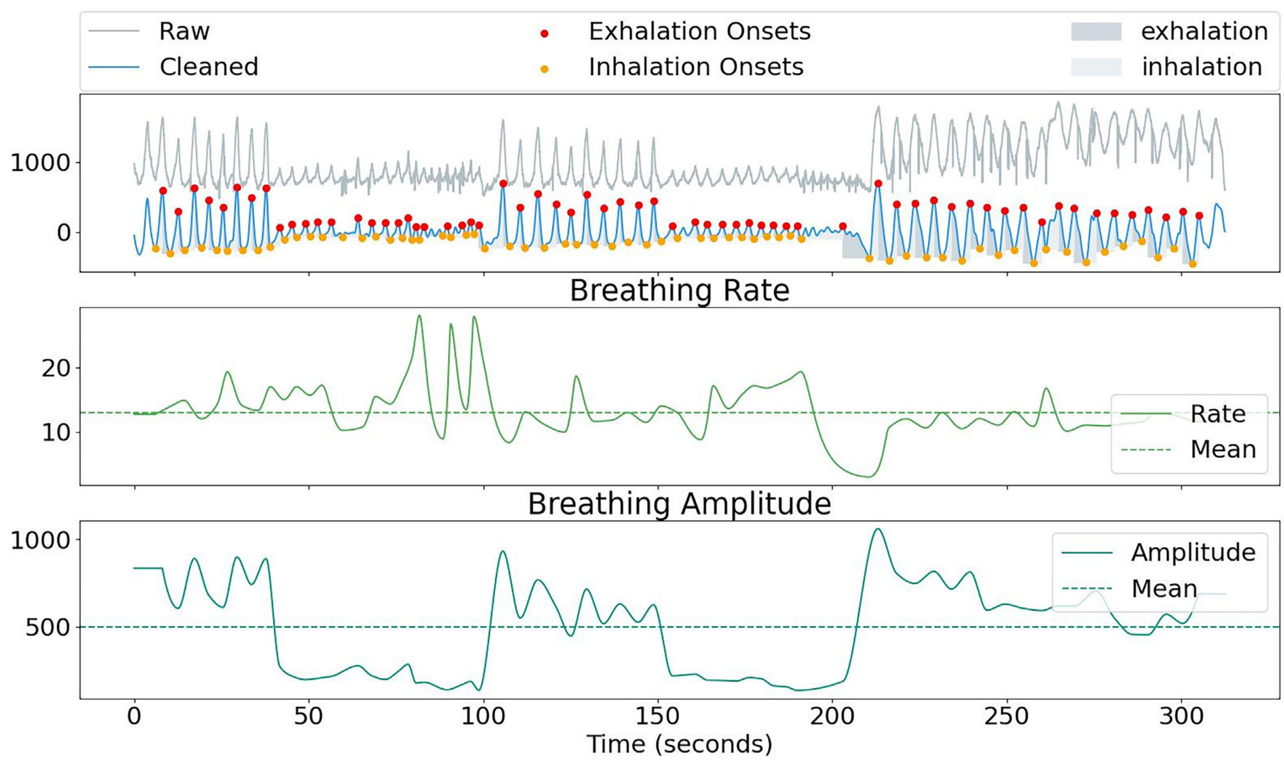

Figure 3. Raw data, filtered data, breathing rate, and breathing amplitude of the data collected from the belt

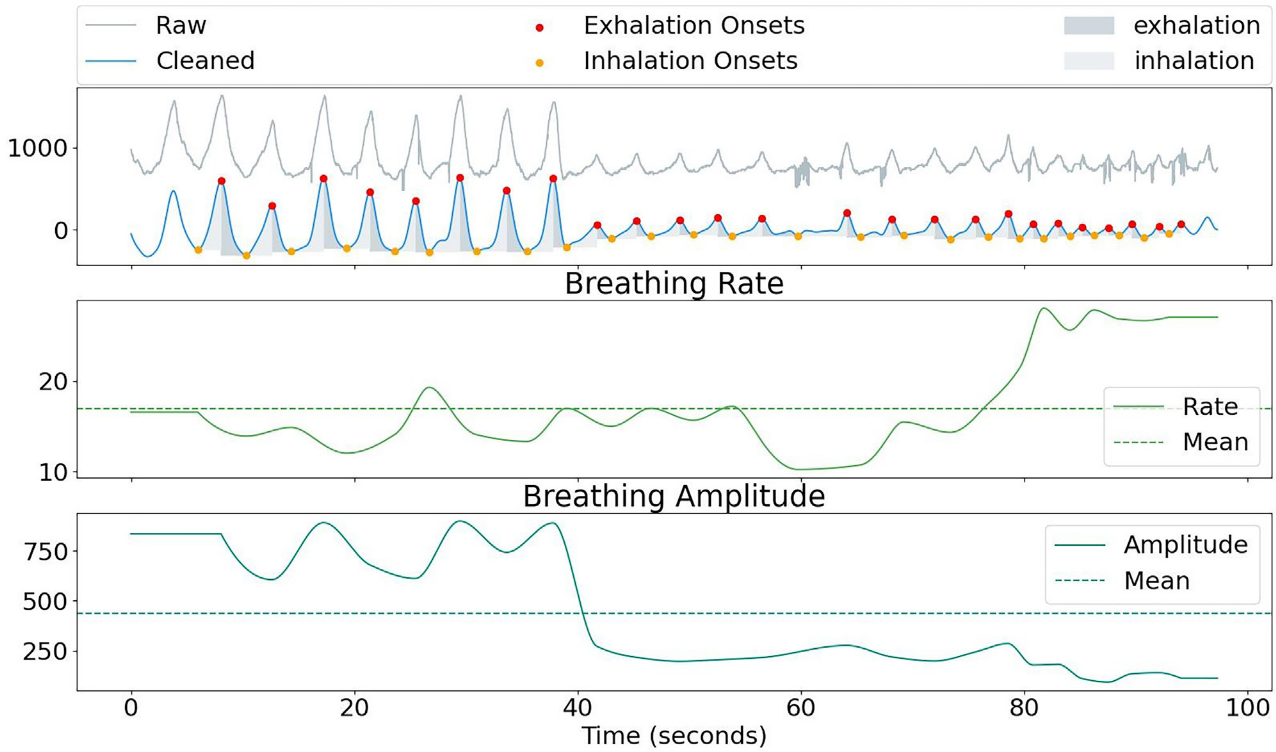

Figure 4. Raw data, filtered data, breathing rate, and breathing amplitude of the data collected from the belt during standing

among others. These sensors differ not only in their technological underpinnings but also in their intended application areas, which can range from clinical diagnostics to experimental research. A critical consideration in their use is the tradeoff between the sensor's characteristics, such as sensitivity and response time, and factors like wearability and comfort for the user. The use of textile-based sensors on health and motion monitoring and increasing their effectiveness were also explored.[49–51]

Moreover, while these systems are capable of monitoring respiration, their effectiveness can be limited by the context in which they are used. For instance, many systems are optimized for specific conditions and postures, such as sitting or lying down, and may not provide accurate data when the subject is in motion or engaging in daily activities like walking or bending. This poses a significant limitation as it does not reflect the dynamic range of human activities and the associated variations in respiratory patterns. Consequently, there is a notable gap in the ability of existing methods to provide comprehensive and accurate monitoring in real-world settings outside of controlled environments.

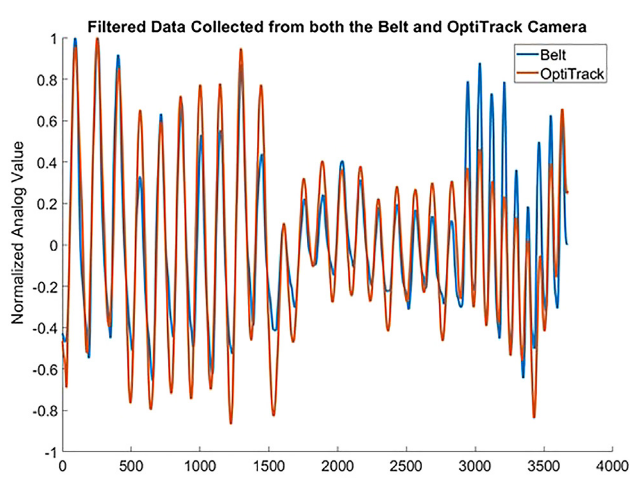

Figure 5. Filtered data collected from belt and camera

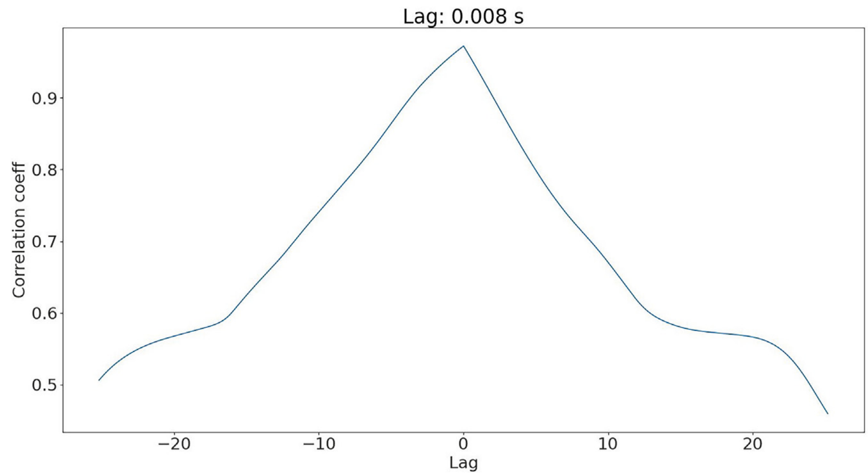

Figure 6. Cross-correlation between respiration date computed using the belt and camera data

This deficiency underscores the need for innovative solutions that can adapt to the variability in human activity and offer reliable monitoring across a spectrum of daily living conditions.

Following our preliminary work,[52] in this article we propose to develop and evaluate an e-textile based respiration monitoring system covering sensor development, data acquisition module, and data acquisition firmware with the evaluation experiment including different postures from daily life and different breathing rates with a comparison with the gold standard camera-based motion capture methods.

A preliminary version of this work has been reported at IEEE sensors conference (2022).[52]

RESULTS AND DISCUSSION

We collected data from our respiration belt and the camera-based system simultaneously in a time synchronized manner. We processed data using the same signal processing pipeline for both sensor data and camera data. We present our comparative analysis in this section.

Characterization of the pressure sensors

Figure 3 shows the raw and filtered signals collected from the middle top sensor on the belt which was the best performed on both belt and OptiTrack. The figure also demonstrates breathing rate and breathing amplitude (the amplitude of the peaks) for the entire experiment for one participant.

To investigate further, the data were also segmented according to the experiment sections (Table S2). The data from slouching posture could not be analyzed due to the lack of performance in OptiTrack system. Figure 4 shows a typical example of the data collected from the belt during the standing section of the experiment.

It is seen that the breathing amplitude and time difference between the peaks decreased when the breathing rate increased. Since fast breathing happens promptly, the magnitude of expansion and contraction of the chest becomes condensed and causes the decrement on the amplitude of breathing signal. The breathing amplitude change on the signal proves that our system can sense those changes accurately.

Evaluation of the sensor belt with the benchmark system

To evaluate our sensor belt system, we compared the data acquired using the sensor belt with the OptiTrack IR cameras. For this, the positional information coming from the cameras was also processed in the same way. Figure 5 shows the filtered data collected from both chest belt and OptiTrack IR cameras. We computed the correlation coefficient between the raw sensor data and the OptiTrack system data. We observed a significant agreement (R value $\geq$0.9) between the data collected by these two systems.

We further investigated the collected data to understand the agreement between the breathing rate extracted using the sensor belt data and the breathing rate extracted using the OptiTrack data. Figure 6 shows the correlation between the breathing rates with respect to the phase lag between the pressure sensors and the camera recorded signals. Here, we found that there was also a significant agreement

Table 1. MAE of respiration rate

	D_stand	N_stand	F_stand	D_sit	N_sit	F_sit	D_bend
MAE	3.25%	12.30%	3.03%	22.91%	11.61%	−0.58%	42.92%

D_stand: Deep breathing in standing position, N_stand: Normal breathing in standing position, F_stand: Fast breathing in standing position, D_sit: Deep breathing in sitting position, N_sit: Normal breathing in sitting position, F_sit: Fast breathing in sitting position, D_bend: Deep breathing in bending position.

Table 2. MAE of respiration rate for each participant

	D_stand	N_stand	F_stand	D_sit	N_sit	F_sit	D_bend
P.1	0.02	2.02	0	10.81	0.71	−49.68	18.76
P.2	0.4	−1.02	−2.27	25.9	5.38	−18.57	1.32
P.3	1.12	7.4	−8.44	−5.17	4.92	0	5.79
P.4	0.33	0.25	10.2	4.28	−1.26	54.24	5.46
P.5	0.69	0.42	0.81	3.16	1.58	−1.78	0.41
P.6	0.36	1.01	5.68	0.62	8.76	3.18	31.85
P.7	0.07	5.52	1.16	0.06	1.29	1.91	4.13
P.8	0.68	1.26	−3.26	0.99	5.26	0.76	7.18
P.9	0.87	8.26	4.52	1.75	0	5.69	1.35
P.10	0.67	1.02	1.62	2.09	1	2.26	11.61

(R value = 0.836) between the respiration rate recorded using our system and the respiration rate recorded using the OptiTrack camera system at almost zero lag position which shows good synchronization between systems. We also computed the mean absolute error (MAE) in the measurement of respiration rate by the sensor belt and the OptiTrack data shown in Table 1. Table 2 shows the MAE for each participant in different positions.

Effects of different postures on the accuracy of the system

In this evaluation study, we also wanted to understand the effects of different postures on the accuracy of breathing rate measured by our system. For that, we conducted experiments to record breathing data in various postures.

It was seen that there were missing data points in the sitting and bending postures in the OptiTrack data. This is because the markers on the chest belt were not detected for a few samples by the OptiTrack IR cameras during certain postures and that have affected the feature extraction process. This situation also caused the MAE for the respiration rate to increase.

It was also observed that the breathing rate during fast breathing increased during the sitting posture compared to standing. This can be attributed to the fact that the sitting posture was more demanding compared to standing, causing an increase in the breathing rate. Figure 7 shows the comparison of the average breathing rate for all participants between different postures.

Wearable DAQ performance

After evaluating the accuracy of our respiration monitoring system, we wanted to understand the system-level timing performance of our in-home designed solution SolunumWear. The idea was to understand how quickly SolunumWear can detect the respiration information which might be critical in certain applications such as apnea detection. For this, we investigated two key parameters related to our system involving time taken for analyzing the respiration signal, and time delay for data transmission.

Time taken for respiration signal analysis

For evaluating the computation time taken to process the respiration signals, we measured the time taken to open CSV files and perform respiration signal processing. Table 3 shows the time taken in seconds to perform signal processing and extract respiration features from

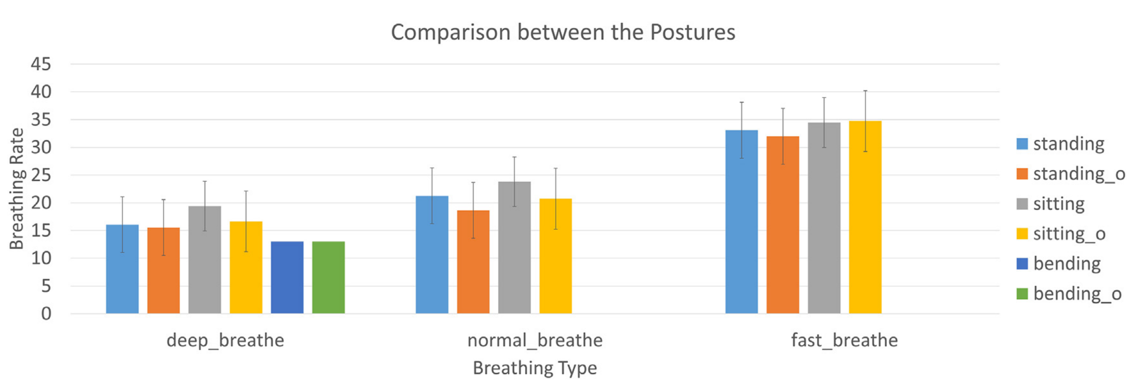

Figure 7. Comparison of different postures

Note: Data are represented as mean and standard error. "o" represents the data from OptiTrack. Bending posture is only present in deep breathing.

Table 3. Respiration signal analysis time

Participant Number	Processing Time (sec)
P.1	4.83
P.2	3.36
P.3	51.81
P.4	4.62
P.5	4.78
P.6	3.98
P.7	7.89
P.8	4.38
P.9	5
P.10	7.20

the signals. We can see that the analysis pipeline is efficient, enabling swift analysis. It was also observed that the time for processing the data collected from P.3 was significantly higher than the others. When we analyzed the data, we found that the missing points in P.3 data were higher than the other, for this reason, the software took more time to fill those points and complete the analysis.

Time delay for data transmission

As respiration events are time-sensitive, the timely transmission of data is of utmost importance. For this reason, we were also interested in evaluating the data transmission time from the sensor belt to the data acquisition and processing module. This evaluation was conducted by logging the round-trip time (RTT) within the transmitter based on the logical voltage state which is set high upon transmission of payload and low upon acknowledgment of receipt of payload by the receiver. We aggregated multiple RTT measurements, and these transmission time measures are shown in Table 4. We could see that the data transmission time (~2 ms) was comparatively lower than the average breathing period which was found to be 2,848 ms.

Comparison with state-of-the-art

Respiratory monitoring has been investigated in recent years. However, obtrusiveness can be used as a factor to determine the user acceptability of different types of systems. Wearable sensors, specifically those to be worn on the face or neck to measure respiration, are more obtrusive compared to the proposed system. Thus, the detection of chest movements is a predominant approach to measure respiration. We compared the efficacy of our system with existing literature. For this, we compared the MAE in recorded respiration rate of our study with the state-of-the-art. Table 5 shows the comparison of MAE in recording breathing rates between existing literature and our study.

It seems that the studies mentioned in the state-of-the-art have focused on developing algorithms to extract respiration rate from various types of sensors such as strain sensors,[54] radar-based measurements,[57] ECG sensors,[53] motion sensors,[48,55] and PPG sensors.[56] While these studies have shown promising results in detecting respiration with almost one breath per minute error, they were not comprehensive enough to mimic real-life conditions as they focused only on different postures or breathing rates at a time, but not both.

For instance, motion sensors were used only to compare different postures such as standing, sitting, and lying down with a constant breathing rate. Similarly, while the strain sensors and ECG sensors were used while walking on a treadmill, the studies did not report the changes in breathing rate. Furthermore, it was noted that strain sensors and ECG sensors may not be the best choice to capture respiration events accurately.

To address this limitation, the comparison made in the current study focused on the MAE of the standing posture with normal breathing (2.614), as well as with deep breathing. Our findings revealed that the MAE for the standing posture with normal breathing closely aligned with previous studies. However, when it came to the standing posture with deep breathing, the MAE (0.521) outperformed the majority of the studies. This highlights the importance of not only assessing differences in postures but also considering variations in breathing rates when conducting evaluations. Overall, findings suggest that future studies should consider different postures along with breathing rates when evaluating the accuracy of sensors in capturing respiration events.

Table 4. RTT-based measurements

Parameter	Time (ms)
Mean	2.13
Median	2.06
Variance	0.53
Maximum RTT	3.42

Table 5. Comparison with state-of-the-art

Study	Mean Absolute Error (MAE)
Cay et al. (This study)	2.614
Boyle et al.[53]	4
Yamamato et al.[54]	3
Hernandez et al.[55]	1.77
Lazaro et al.[56]	1.27
Hernandez et al.[48]	0.72
Zeng et al.[57]	0.28

Limitations of the study

One of the limitations of our current work is the location and placement of the 3D camera markers. Since four of the sensors were located in the armpits, the markers were also placed in the same area. This resulted in occlusion of such markers from the OptiTrack cameras particularly in male participants for certain postures. We plan to change the size and length of the markers to make them more visible to the cameras. Also, the sitting and bending movements created extra movement data which needed to be excluded from the respiration rate extraction. To overcome this, a reference marker will be placed on the region without movement during the breath. Also, in real-life settings, to account for the movement artifacts in the respiration data, we aim to include an inertial measurement unit (IMU) sensor in the belt which we lack in our current system. Since this is our pilot work, the IMU sensor was not included in the belt design. In the future, we plan to add an IMU sensor to evaluate the changes for different postures and extract the noise profile during the sitting and bending movements. In addition, our current setting is within the lab setup to use OptiTrack cameras which limits our experiment with sport motion such as walking or jogging. In our future studies, we are planning to test our belt in daily life settings by giving it to participants for wearing during their day and nighttime and extracting the motion noise profile with the IMU sensors. We also want to address another shortcoming related to the size of the hardware. Initially, in our prototype, the hardware was positioned at the belt's rear, attached to the strap. In the revised design, our goal is to reduce the hardware's dimensions so it can be integrated within the belt and entirely encased in fabric.

Conclusion

In this paper, we presented a wireless, smart textile-based respiration monitoring system called SolunumWear. We developed a sensor belt for adults that covers the chest area, a wearable data acquisition system, and established wireless communication between the wearable data acquisition system and the computer which is used to process the data. We also used the OptiTrack camera system as a benchmark to compare our system i.e., SolunumWear. To evaluate the performance of SolunumWear, we recruited 10 healthy adults. Our findings showed that SolunumWear can sense the different respiration rates (even in different postures) accurately and reliably.

Nevertheless, our results showed that SolunumWear can be used for monitoring the respiration changes and effects of different postures on the respiration rates on different body types and different genders. Therefore, SolunumWear can be a reliable candidate for monitoring in pulmonary rehabilitation, COVID rehabilitation, or apnea monitoring. In addition, since it is a completely wearable, battery-operated, and wireless system, SolunumWear can also be used for in-home patient monitoring and management for pulmonary diseases.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2024.110223.

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AUTHOR CONTRIBUTIONS

G.C., D.S., and K.M. conceived the presented idea. G.C. and M.A.A. fabricated the e-textile chest belt. G.C. and K.F. carried out the experiment with support from V.R., who integrated the camera system. G.C., V.R., and D.S. analyzed the data. K.M. and D.S. supervised the project. G.C. created the initial draft. All authors discussed the results and contributed to the final manuscript.

DECLARATION OF INTERESTS

G.C. is now with Baylor College of Medicine as a postdoctoral associate. However, her contributions to human study, data collection, and data analysis were limited to when she was a PhD researcher at the University of Rhode Island. K.O.F. is now at Louisiana Tech University. However, her contributions to this study were limited to when she was a visiting scholar with the University of Rhode Island. K.M. is a co-founder of WellAware Research LLC. He confirms that the work presented in this journal article is entirely independent of his responsibilities and role at the company. He has no financial or personal interests that could inappropriately influence, or be perceived to influence, the content of the research, review, or editorial process associated with this manuscript. D.S. has transitioned from his role as a postdoctoral researcher to an Assistant Professor at the University of Rhode Island. This change does not affect the integrity of the research in this manuscript with no financial or personal interest that could bias the work.

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REFERENCES

1. Aleksandar, M., Chris, O., and Emil, J. (2006). Wireless sensor networks for personal health monitoring: Issues and an implementation. Comput. Commun. *29*, 2521–2533. https://doi.org/10.1016/j.comcom.2006.02.011.
2. Christian Peter, S., and Sean, K. (2018). Continuous monitoring of respiratory rate in emergency admissions: evaluation of the RespiraSense™ sensor in acute care compared to the industry standard and gold standard. Sensors *18*, 2700. publisher = Multidisciplinary Digital Publishing Institute.
3. Xiufeng, Y., Zhihao, C., Chia Ser Ming, E., Lam Hong Ying, J., Soon Huat, N., Ju Teng, T., and Ruifen, W. (2014). Textile fiber optic microbend sensor used for heartbeat and respiration monitoring. IEEE Sensor. J. *15*, 757–761. publisher = IEEE.
4. Ikuo, H., and Yuri, M. (2008). Breathing rhythms and emotions. Exp. Physiol. *93*, 1011–1021. publisher = Wiley Online Library.
5. Marco, G. (2017). Emotions Recognition in Video Game Players Using Physiological Information (University of Milan). https://air.unimi.it/bitstream/2434/607597/4/phd_unimi_R11403.pdf.
6. Xin, L., Qisong, W., Dan, L., Yuan, W., Yan, Z., Ou, B., and Jinwei, S. (2018). Human emotion classification based on multiple physiological signals by wearable system. Technol. Health Care *26*, 459–469. publisher = IOS Press.
7. Zdzisław, K., Michał, C., and Tomasz, M. (2019). Emotion monitoring system for drivers. IFAC-PapersOnLine *52*, 200–205. publisher = Elsevier.
8. Vera Eva, Z. (2018). Back to the roots: the role of sensory sensitivity and respiration pattern variability in mental health (Doctoral dissertation).
9. Dijana, Ć. (2016). Neuromarketing in market research. Interdiscip. Descr. Complex Syst. *14*, 139–147. publisher = Hrvatsko interdisciplinarno društvo.
10. Angelica, M.T., Tycho, T.d.B., and Max, M.L. (2020). Neurophysiological changes in visuomotor sequence learning provide insight in general learning processes: Measures of brain activity, skin conductance, heart rate and respiration. Int. J. Psychophysiol. *151*, 40–48. publisher = Elsevier.
11. Krishna, M., Simon, S., Brown, T., Bann, S., and Darzi, A. (2003). Evaluation of virtual reality bronchoscopy as a learning and assessment tool. Respiration *70*, 195–199. publisher = Karger Publishers.
12. Czub, M., and Kowal, M. (2019). Respiration entrainment in virtual reality by using a breathing avatar. Cyberpsychol., Behav. Soc. Netw. *22*, 494–499. publisher = Mary Ann Liebert, Inc., publishers 140 Huguenot Street, 493rd Floor New ….
13. Pavithra, R., Na-Teng, H., Thenkurussi, K., John, V., and Praveen, K. (2018). AirwayVR: learning endotracheal intubation in virtual reality. In 2018 IEEE conference on virtual reality and 3D user interfaces (VR).
14. Billy, S., Kamiar, A., Peter, D., and Hans-Christer, H. (2020). Wearable Sensor Technology for Monitoring Training Load and Health in the Athletic Population. Front. Physiol. *10*, 1520. publisher = Frontiers.
15. Gozde, C., Vignesh, R., Manob Jyoti, S., Laurie, H., Abbot, L., James, P., Amy, L.S., Anna, G.-K., Krishna, V., and Yalda, S. (2022). An E-Textile Respiration Sensing System for NICU Monitoring: Design and Validation. J. Signal Process. Syst. *94*, 543–557. https://doi.org/10.1007/s11265-021-01669-9.
16. Chukwudi, E. (2020). Auscultation of the lungs. https://3d4medical.com/blog/auscultation-of-the-lungs.
17. Whited, L., Hashmi, M.F., and Graham, D.D. (2023). Abnormal Respirations (StatPearls Publishing).
18. John, M.S. (2009). Sleep medicine: a guide to sleep and its disorders (John Wiley & Sons).
19. Phil, C., and Esther, R.-V. (2007). Breathing detection: towards a miniaturized, wearable, battery-operated monitoring system. IEEE (Inst. Electr. Electron. Eng.) Trans. Biomed. Eng. *55*, 196–204. publisher = IEEE.
20. Werthammer, J., Krasner, J., DiBenedetto, J., and Stark, A.R. (1983). Apnea monitoring by acoustic detection of airflow. Pediatrics *71*, 53–55. pmid = 6848979.
21. Martin, J.T. (1988). Respiratory monitoring in the intensive care unit12. Amer. Rev. Respir. Dis. *138*, 1625–1642.
22. Mia, F., Fredrik, G., Bertil, H., and Håkan, S. (2002). Comparative provocation test of respiratory monitoring methods. J. Clin. Monit. Comput. *17*, 97–103. publisher = Springer.
23. Storck, K., Karlsson, M., Ask, P., and Loyd, D. (1996). Heat transfer evaluation of the nasal thermistor technique. IEEE Trans. Biomed. Eng. *43*, 1187–1191. pmid = 9214837. https://doi.org/10.1109/10.544342.

24. Teofilo, L.L.-C. (2005). Sleep: a comprehensive handbook (Wiley-Liss), pp. 73–78.
25. Kundan, N., Biegeleisen, E., and Taikang, N. (2002). Apnea detection and respiration rate estimation through parametric modelling. In Proceedings of the IEEE 28th Annual Northeast Bioengineering Conference (IEEE Cat. No.02CH37342), pp. 277–278.
26. Oscar, H.M., Russell, G.C.,S., Abbas, F.J., Joseph, M.M., and Julian, L.A. (2003). Respiratory inductance plethysmography in healthy 3-to 5-year-old children. Chest *124*, 1812–1819. publisher = Elsevier.
27. Prisk, G.K., Hammer, J., and Christopher, J.L.N. (2002). Techniques for measurement of thoracoabdominal asynchrony. Pediatr. Pulmonol. *34*, 462–472. publisher = Wiley Online Library.
28. Strömberg, N.O.T., and Nina, N. (1998). Thoracoabdominal asynchrony in small children with lung disease–methodological aspects and the relationship to lung mechanics. Clin. Physiol. *18*, 447–456. publisher = Wiley Online Library.
29. Leonard, P., Beattie, T.F., Addison, P.S., and Watson, J.N. (2003). Standard pulse oximeters can be used to monitor respiratory rate. Emerg. Med. J. *20*, 524–525. publisher = British Association for Accident and Emergency Medicine.
30. Wertheim, D., Olden, C., Savage, E., and Seddon, P. (2009). Extracting respiratory data from pulse oximeter plethysmogram traces in newborn infants. Arch. Dis. Child. *94*, F301–F303. https://doi.org/10.1136/adc.2008.145342.
31. Ciara, O.B., and Conor, H. (2007). A comparison of algorithms for estimation of a respiratory signal from the surface electrocardiogram. Comput. Biol. Med. *37*, 305–314. publisher = Elsevier.
32. George, B.M., Roger, G.M., Marjorie, A.B., Joseph, S.W., Aaron, D.B., Joseph, E.M., and Ary, L.G. (1986). Clinical validation of the ECG-derived respiration (EDR) technique. Comput. Cardiol. *13*, 507–510. publisher = IEEE Computer Society Press.
33. Mazzanti, B., Lamberti, C., and Bie, J.D. (2003). Validation of an ECG-derived respiration monitoring method. Comput. Cardiol. *2003*, 613–616.
34. Shuxue, D., Xin, Z., Wenxi, C., and Daming, W. (2004). Derivation of respiratory signal from single channel ECGs based on source statistics. Int. J. Bioelectromagn. *6*, 43–49.
35. Tarassenko, L., Mason, L., and Townsend, N. (2002). Multi-sensor fusion for robust computation of breathing rate. Electron. Lett. *38*, 1314–1316. publisher = IET.
36. Kazuki, N., Yoshiaki, M., and Toshiyo, T. (2001). Development of real-time image sequence analysis for evaluating posture change and respiratory rate of a subject in bed. Physiol. Meas. *22*, N21. publisher = IOP Publishing.
37. Mari, Z., Harri, R., and Jukka, V. (2011). Comparison of center estimation algorithms for heart and respiration monitoring with microwave Doppler radar. IEEE Sensor. J. *12*, 627–634. publisher = IEEE.
38. Tan, K.S., Reza, S., Heather, E., and Derek, B. (2010). Real-time vision based respiration monitoring system. In 2010 7th International Symposium on Communication Systems, Networks \& Digital Signal Processing (CSNDSP 2010).
39. Cheung-Hwa, H., and Julie Chi, C. (2005). Design and clinic monitoring of a newly developed non-attached infant apnea monitor. Biomed. Eng. Appl. Basis Commun. *17*, 126–134. publisher = World Scientific.
40. Farah, Q.A.-K., Reza, S., Derek, B., and Heather, E. (2010). Facial tracking method for noncontact respiration rate monitoring. In 2010 7th International Symposium on Communication Systems, Networks \& Digital Signal Processing (CSNDSP 2010).
41. Sergey Yu, C., Helen, R., and Aly, A.F. (2005). Non-contact, wavelet-based measurement of vital signs using thermal imaging. In The first international conference on graphics, vision, and image processing (GVIP), Cairo, Egypt.
42. Zhen, Z., Jin, F., and Ioannis, P. (2005). Tracking human breath in infrared imaging. In Fifth IEEE Symposium on Bioinformatics and Bioengineering (BIBE'05).
43. Farah, A.-K., Reza, S., Heather, E., and Derek, B. (2011). An evaluation of thermal imaging based respiration rate monitoring in children. Am. J. Eng. Appl. Sci. *4*, 586–597. publisher = Science Publications.
44. Farah, Q.A.-K., Reza, S., Derek, B., and Heather, E. (2010). Tracking human face features in thermal images for respiration monitoring. In ACS/IEEE International Conference on Computer Systems and Applications-AICCSA 2010.
45. Cobos-Torres, J.-C.A., and Martinez-Orgado, M. (2018). Non-Contact, Simple Neonatal Monitoring by Photoplethysmography. Sensors *18*, 4362. https://doi.org/10.3390/s18124362.
46. Longmore, S.K.L., Naik, G.Y., Breen, G., Paul, P.J., Bin, G., and Gaetano, D. (2019). A Comparison of Reflective Photoplethysmography for Detection of Heart Rate, Blood Oxygen Saturation, and Respiration Rate at Various Anatomical Locations. Sensors *19*, 1874. https://doi.org/10.3390/s19081874.
47. Michael, C., Thao, N., Vaibhav, P., Yongxiao, Z., Hoang, N.P., Ronen, B.-Y., Shlomit, R.-A., Ramesh, J., Dan, M.C., and Michelle, K. (2019). Respiration rate and volume measurements using wearable strain sensors. npj Digit. Med. *2*, 8. https://doi.org/10.1038/s41746-019-0083-3.
48. Hernandez, J., McDuff, D., and Picard, R.W. (2015). Biowatch: Estimation of heart and breathing rates from wrist motions. In 2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) (IEEE), pp. 169–176.
49. Tang, J., Wu, Y., Ma, S., Yan, T., and Pan, Z. (2022). Sensing mechanism of a flexible strain sensor developed directly using electrospun composite nanofiber yarn with ternary carbon nanomaterials. iScience *25*, 105162. https://doi.org/10.1016/j.isci.2022.105162.
50. Tang, J., Wu, Y., Ma, S., Zhang, Y., Xu, R., Yan, T., and Pan, Z. (2024). Fabricating a smart clothing system based on strain-sensing yarn and novel stitching technology for health monitoring. Sci. China Technol. Sci. *67*, 587–596. https://doi.org/10.1007/s11431-023-2442-9.
51. Zhao, L., Qiao, J., Li, F., Yuan, D., Huang, J., Wang, M., and Xu, S. (2022). Laser-Patterned Hierarchical Aligned Micro-/Nanowire Network for Highly Sensitive Multidimensional Strain Sensor. ACS Appl. Mater. Interfaces *14*, 48276–48284. https://doi.org/10.1021/acsami.2c14642.
52. Solanki, D., Cay, G., Al Rumon, M.A., Ravichandran, V., and Mankodiya, K. (2022). A Step Towards Design and Validation of a Wearable Multi-Sensory Smart-Textile System for Respiration Monitoring. In *2022 IEEE Sensors* (IEEE), pp. 1–4.
53. Boyle, J., Bidargaddi, N., Sarela, A., and Karunanithi, M. (2009). Automatic Detection of Respiration Rate From Ambulatory Single-Lead ECG. IEEE Trans. Inf. Technol. Biomed. *13*, 890–896. https://doi.org/10.1109/TITB.2009.2031239.
54. Yamamoto, A., Nakamoto, H., Bessho, Y., Watanabe, Y., Oki, Y., Ono, K., Fujimoto, Y., Terada, T., and Ishikawa, A. (2019). Monitoring respiratory rates with a wearable system using a stretchable strain sensor during moderate exercise. Med. Biol. Eng. Comput. *57*, 2741–2756. mendeley-groups = Frontiers. https://doi.org/10.1007/s11517-019-02062-2.
55. Hernandez, J., Li, Y., Rehg, J.M., and Picard, R.W. (2014). BioGlass: Physiological parameter estimation using a head-mounted wearable device. In 2014 4th International Conference on Wireless Mobile Communication and Healthcare-Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH) (IEEE), pp. 55–58.
56. Lazaro, J., Gil, E., Bailn, R., and Minchol. (2013). Deriving respiration from photoplethysmographic pulse width. Med. Biol. Eng. Comput. *51*, 233–242. mendeley-groups = CHI,Frontiers. https://doi.org/10.1007/s11517-012-0954-0.
57. Zeng, Y., Wu, D., Xiong, J., Yi, E., Gao, R., and Zhang, D. (2019). FarSense: Pushing the Range Limit of WiFi-Based Respiration Sensing with CSI Ratio of Two Antennas. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. *3*, 1–26. https://doi.org/10.1145/3351279.
58. ZSK Embroidery Machines. 2024, https://www.zskmachines.com/.
59. (2024). esp-now. https://docs.espressif.com/projects/esp-idf/en/latest/esp32/api-reference/network/esp_now.html.
60. Roger Meier's Freeware. 2024, https://freeware.the-meiers.org/.
61. Flex 13. 2024, https://optitrack.com/cameras/flex-13/.
62. Raffaele, L.D., Maria, L.V., Emanuela, Z., Miria, N., Antonio, P., and Paolo, T. (2010). Measurement of total and compartmental lung volume changes in newborns by optoelectronic plethysmography. Pediatr. Res. *67*, 11–16. publisher = Nature Publishing Group.
63. Igor, T., Willem-Paul, W., Maarten, B., and Rob, L. (2020). Validity of a New 3-D Motion Analysis Tool for the Assessment of Knee, Hip and Spine Joint Angles during the Single Leg Squat. Sensors *20*, 4539. publisher = Multidisciplinary Digital Publishing Institute.
64. Motive. Optical motion capture software. 64. https://optitrack.com/software/motive/.
65. Makowski, D., Pham, T., Lau, Z.L., Brammer, J.C., Lespinasse, F., Pham, H., Schölzel, C., and Chen, S.H.A. (2021). NeuroKit2: A Python toolbox for neurophysiological signal processing. Behav. Res. Methods *53*, 1689–1696. https://doi.org/10.3758/s13428-020-01516-y.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
ESP-Now	https://docs.espressif.com/projects/esp-idf/en/latest/esp32/api-reference/	
NeuroKit2 library software	Makowski et al.[65]	

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Gozde Cay (gozdecay@uri.edu).

Materials availability

This study did not generate new unique reagents.

Data and code availability

All data reported in this article will be shared by the lead contact on request.
This article does not report the original code.
Any additional information required to reanalyze the data reported in this article is available from the lead contact on request.

METHOD DETAILS

We designed the SolunumWear system which consisted of (a) an in-lab developed textile-based pressure sensors, (b) a chest belt housing the pressure sensors and the wearable data acquisition unit, and (c) a telemonitoring communication module. Each of these modules are discussed in the following sections.

Design of the pressure sensors

The embroidered pressure sensors were created based on the method that we used in[15,52] using Velostat material and conductive thread. Velostat is a piezoresistive material that changes its resistance upon application of lateral pressure. During breathing the chest moves along the frontal plane resulting in pressure changes on the Velostat material. To collect those resistance changes, a silver-coated conductive thread was utilized (Madeira HC-40, <300 ohm/meter). The resistance change due to pressure was measured using a voltage divider circuit. Supply voltage was applied on one terminal of the pressure sensor while the other end was connected both to the measurement terminal and a standard resistor that was connected to ground.

The sensor construction involved two major steps. First, the conductive thread was embroidered over two denim fabric layers as seen in Figure S1A (top) and S1c (bottom) with an industrial technical embroidery machine.[58] The denim fabric provides enough elasticity which holds the pressure on the sensor. Next, the Velostat material (0.1mm thick, Volume Resistivity: <500 ohm-cm, Surface Resistivity: <31,000 ohms/sq.cm) was placed between the top and bottom layers creating a sandwich structure as seen in Figure S1B. Our previous study indicated that a perpendicular stitch pattern produces maximum resistance change for applied pressure.[15]

To achieve a reliable data collection, different designs were considered for the placement of conductive threads and the Velostat material. The conductive thread needed to be stitched in a way which creates less resistance and more conductivity, but it also needs to be resistive enough to carry the changes in Velostat material due to the pressure changes. For this reason, different stitch properties such as the step length, stitch length, number of runs on the thread were tested and we ended up with the design which is shown in Figure S1. To provide enough resistivity, conductive lines were stitched in the shape that covers the surface of Velostat with 0.1-inch spaces between the lines. In addition, a separate line was added to make the dimension between pressure point and the snap connector shorten to provide more conductivity. Six separate sensor pads were created with this design individually. Figure S1 shows the individual components associated with developing a single sensor unit.

Design of the chest belt

In this study, we designed a chest belt for adults by considering the differences between babies' bodies and adults' bodies. The chest belt consisted of two major elements involving (i) the sensor integrated smart textile belt and (ii) the wireless embedded system to collect data from the sensors.

i. **Integration of the Pressure Sensors:** The respiratory cycle (inhalation and exhalation) causes movement in the entire chest area. The magnitude of movement varies from person to person including the differences in gender, body dimensions, height, and structure. Therefore, to achieve accurate respiration detection, the entire chest area needs to be monitored. Designing a singular or dual-sensor configuration to encompass the entirety of the chest area posed a significant challenge, primarily owing to the chest's curved morphology. Ensuring close contact with the skin is imperative for these sensors, and the singular or dual-sensor designs did not effectively achieve this due to the chest's contour. To address this issue, we opted for a multi-sensor approach, which yielded favorable results. Placing sensors both in the central region of the chest and on the lateral sides of the chest was found to be the most effective strategy for achieving the desired level of skin-sensor contact. Thus, we placed a total of six pressure sensors covering almost the entire chest region. A set of three sensors was placed on the upper chest area and another set was placed on the lower chest area. The sensors were placed at the center and the sides of the chest as shown in Figure S2.

To integrate the sensors into the chest belt, we sewed another fabric between the sensors. It is crucial to understand that for accurately detecting variations in pressure from chest movements, the belt needs to make contact with the chest and fit closely. Nonetheless, if the belt is overly tight, it could lead to discomfort for the user or participant, as well as potentially skew the pressure data. For this reason, a stable fabric was chosen to provide the tightness of the belt and make it fit to the body. It is also known that every adult has a different body and chest size. It means that the chest belt needs to be adjustable to make sure that the sensors are in the correct same position for each individual. To accommodate different chest sizes, the chest belt was created based on the largest size, then the black fabric between the sensor pads was folded and clipped with fabric clips according to the smaller sizes such as medium, small, and extra small. For the back side of the belt, a Velcro stripe was used to provide adjustability. Based on these adjustments, the chest belt can be used on both females and males. Figure S2A shows the chest belts integrated with sensors.

ii. **Integration of the Wearable Data Acquisition System:** SolunumWear was designed to be used in day-to-day life. Thus, it was important to collect data from the system which does not hinder one's movements. To achieve this, a wearable data acquisition system (W-DAQ) which could collect the data from the pressure sensors and send the data wirelessly to the computing device was developed. The W-DAQ consisted of an ESP-32 based microcontroller, a 16-bit analog-to-digital converter (ADC), a battery monitor module and a 3.7 Li-Po battery. All components were combined on a PCB and connected to the chest belt using wires. Figure S3 shows the chest belt with the W-DAQ and Figure S4 shows the components of W-DAQ.

Design of the telemonitoring communication system

Wireless data acquisition is performed over the ESP-Now, a 2.4GHz wireless communication protocol. ESP-Now is a protocol designed specifically for ESP32 and ESP8266 microcontrollers that encapsulates message payloads and then transmits it over the Wi-Fi to the receiver ESP32 microcontroller.[59] The receiver device is connected to the edge computing device (ECD) using a USB cable and it communicates incoming payloads from the chest belt over USB-serial. A laptop running Windows 10 was used in this case as the ECD due to the ubiquitous availability of the USB protocol. However, other lower power single board computers such as tablets, Raspberry Pi etc. can be utilized as an ECD. The CoolTerm program was used in the ECD to log the USB serial data to a CSV file for analysis.[60]

Experimental setup

Our experiments were designed to monitor the respiration rate and respiration changes in different postures. We conducted experiments to evaluate respiration sensor performance and to evaluate performance of the wireless data acquisition system as well.

Respiration sensor validation

The chest belt was placed on the participants' chest and adjusted according to different body sizes as shown in Figure S2. In addition, Flex 13 OptiTrack marker-based motion capture was used as the ground truth for measuring precise movement of different points on the chest associated with breathing.[61] Prior studies have seen its utilization for human motion analysis and a study conducted by Dellaca et al. shows the capability of the marker-based motion tracking systems in acquiring lung movement associated with neonatal breathing.[62,63] The OptiTrack motion tracking system used in this study acquires live video streams at 100 frames per second from multiple infrared cameras. The individual camera units are mounted on a tall tripod using custom 3D printed mounts. The cables are routed to the OptiHub unit that synchronizes and multiplexes camera video streams and connected to the host computer using two USB cables. The IR LEDs illuminate the reflective markers enabling its 3D positions to be tracked using the OptiTrack's Motive software running on the host computer.[64] In our study, the reflective markers were placed on the belt, next to the sensors as shown in Figure S5. Synchronization between the chest belt sensors and OptiTrack system is enabled through the use of the External Device Sync connector in the OptiHub. The connector outputs a TTL signal with logical voltage going high state when recording is begun and low state when recording is ended. Using a BNC cable, we are able to read the state using an interrupt within the transmitter ESP32 microcontroller at the start of the recording session. The firmware within the ESP32 was configured to only transmit sensor payloads at the start of recording.

The chest sizes were determined according to the measurements taken from different people. 10 participants (6 female, 4 male, average age = 27.2) with different chest sizes were recruited in this study. They gave signed and informed consent to participate. The study protocol was approved by the University of Rhode Island Institutional Review Board (protocol number is 1785106-6). Participant's chest size information was shown in Table S1. Participants were asked to perform standing, sitting, bending, and slouching postures in between the cameras as shown in Figure S6. The data from IR cameras and our system were captured in a time synchronized manner. The experimental protocol is explained in Table S2.

Signal processing and respiration rate calculation

The data was analyzed using NeuroKit2 library software.[65] To analyze the different breathing rates, the raw data coming from the pressure sensors was filtered using a band-pass filter with cut-off frequencies as 0.05-0.7 Hz (selected based on the human breathing rate range). Subsequently, we applied a peak detection algorithm over the filtered data to monitor breathing as each breathing period (inhalation and exhalation) creates a peak in the data. Then, we computed the time interval (T) between each peak and by using the time interval between two consecutive peaks (T), the breathing rate (RR) was calculated using Equation 1. The same process applied for both signals coming from the chest belt and OptiTrack.

$$RR = \frac{60000}{T} \quad \text{(Equation 1)}$$

Wearable DAQ evaluation setup

Timing measures between the sender and receiver were used to evaluate the wireless transmission system performance. We use a dual-channel oscilloscope to visualize the state of two digital pins within the receiver and transmitter ESP32 device. By setting the pin states to high right after the transmission of the payload and low after confirmation of payload receipt, we were able to log the time associated with transmission. This test was conducted while the chest belt and receiver were separated by 5 meters with an oscilloscope connected between them.