ADVANCED FUNCTIONAL MATERIALS

Supporting Information

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Stretchable Composite Acoustic Transducer for Wearable Monitoring of Vital Signs

Yasin Cotur, Michael Kasimatis, Matti Kaisti, Selin Olenik, Charis Georgiou, and Firat Güder**

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Department of Bioengineering, Imperial College London, SW7 2AZ, United Kingdom

*Corresponding Authors: guder@imperial.ac.uk and y.cotur16@imperial.ac.uk

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1. Figures

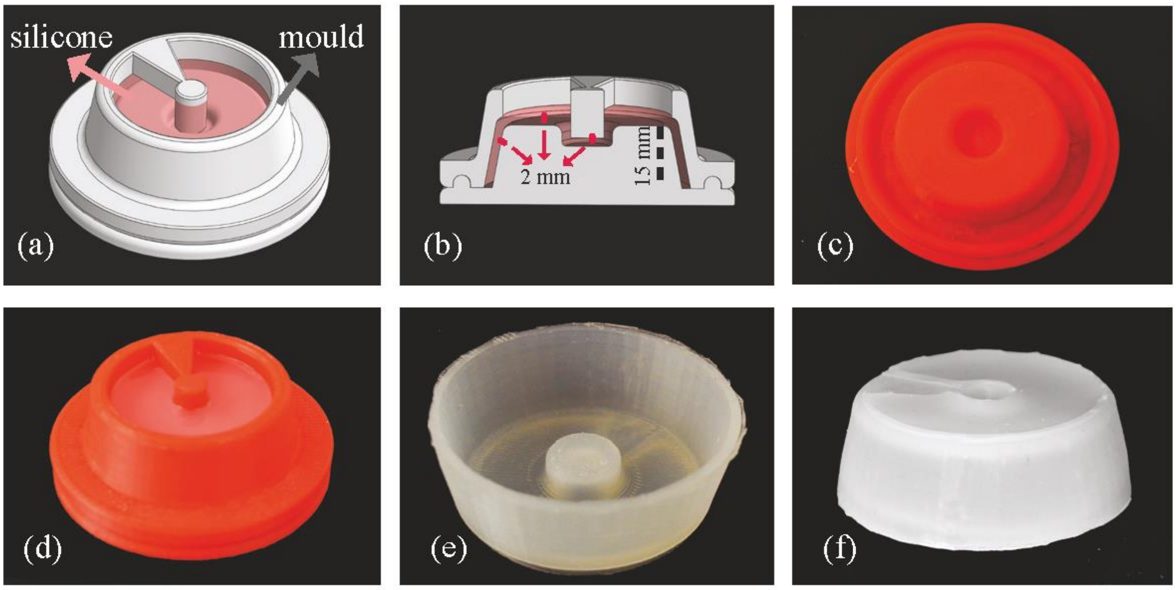

Figure S1. Design of the molds inspired by a commercial stethoscope diaphragm and steps of fabrication; (**a**) Schematic of the molds used for fabrication; (**b**) Cross-sectional view of (a). The thickness of the silicone rubber is 2 mm and height of the diaphragm is 15 mm; (**c**) Top and **(d)** isometric photographic views of the 3D printed PLA mold. The mold (d) contains a silicone mold made of PLA material using a 3D printer; (**e**) Partially-cured silicone rubber which is filled with water in the subsequent step to create the final device; (**f**) The final water-silicone composite diaphragm.

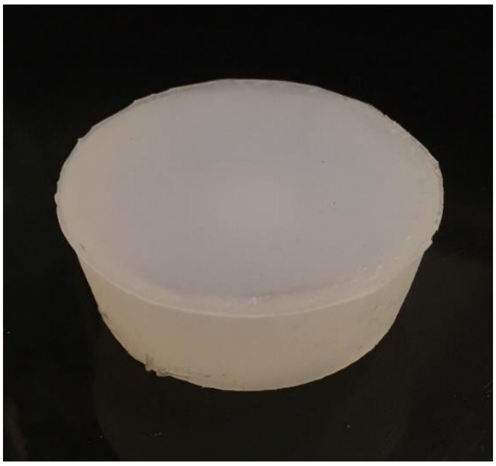

Figure S2. Hydrogel-silicone composite transducer.

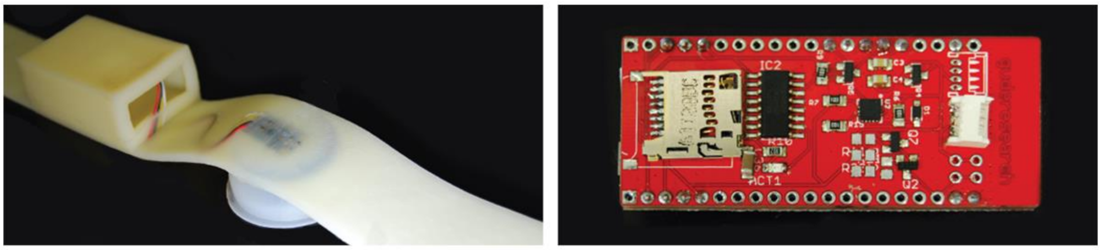

Figure S3. **(Left)** Water-silicone composite transducer monolithically integrated into a silicone-based stretchable and flexible harness. The complete wearable harness contains electronics **(Right)** and is capable of collecting, transmitting and storing audio recordings. The audio amplifier and its wires are encased with silicone to reduce environmental noise and to create a mechanically robust system. The wires from the audio amplifier to the electronics are placed in a zigzag shape to allow stretching.

Figure S4. Re-recording of the reference heart sounds (downloaded from an online repository) using a loudspeaker. Re-recording with a **(Left)** commercial stethoscope; **(Right)** 15 mm water-silicone composite transducer.

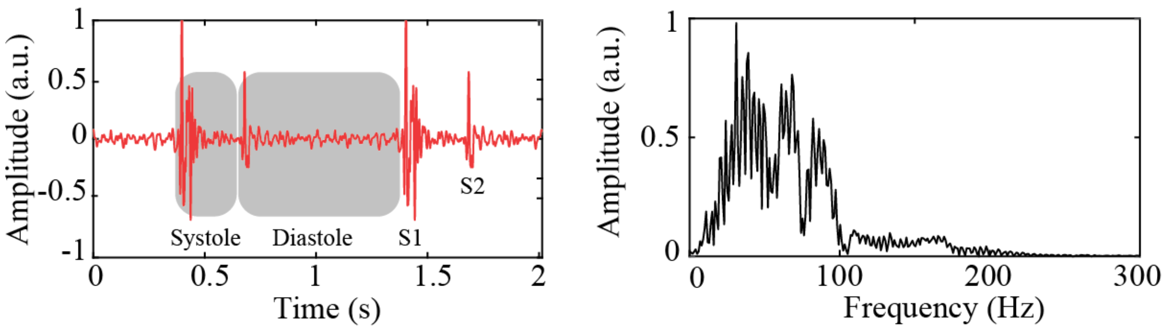

Figure S5. Time and frequency domain descript of the reference heart sounds downloaded from the online repository.

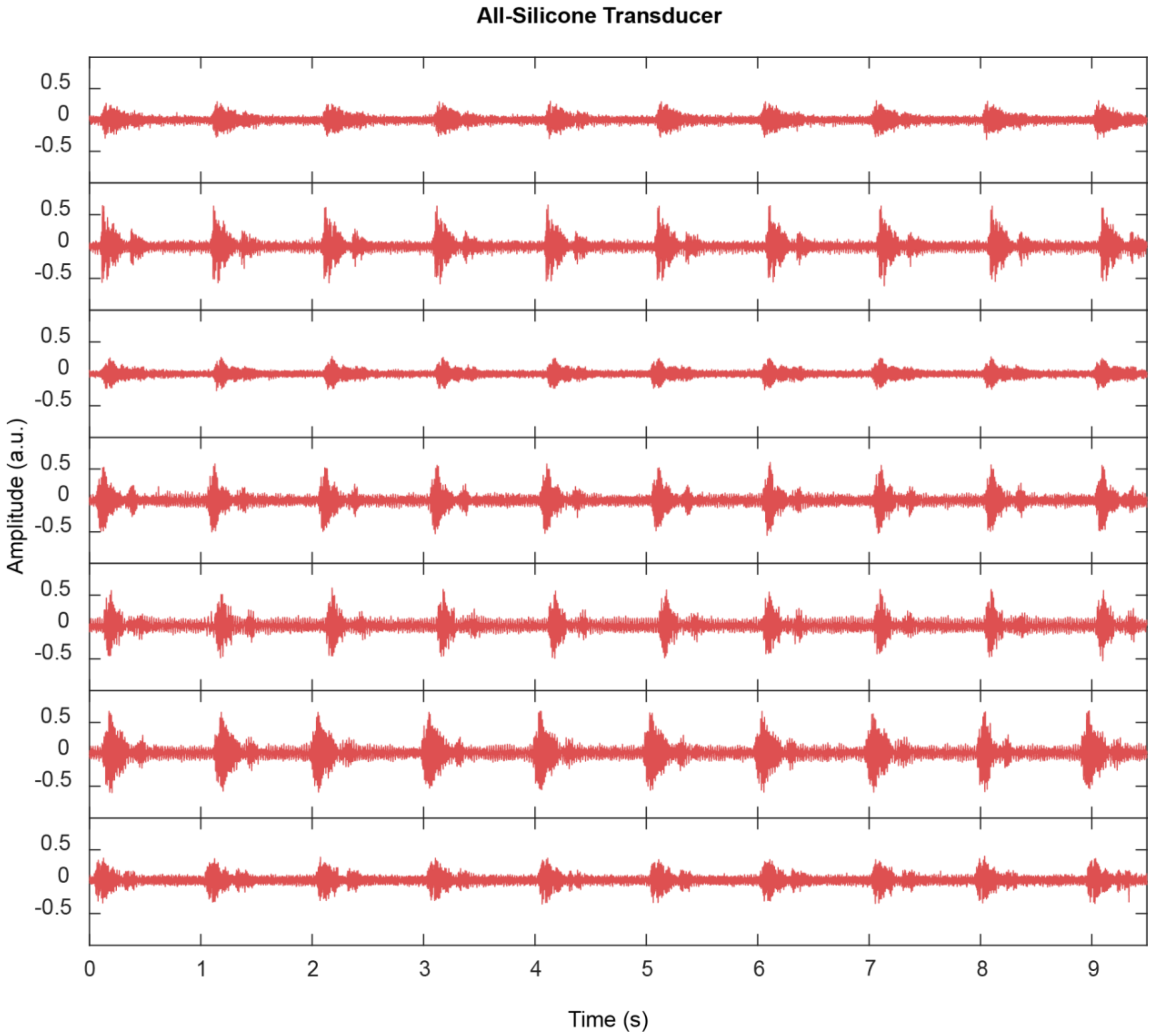

Figure S6. Re-recorded waveforms of the reference recording from seven different all-silicone transducers with a height of 15 mm.

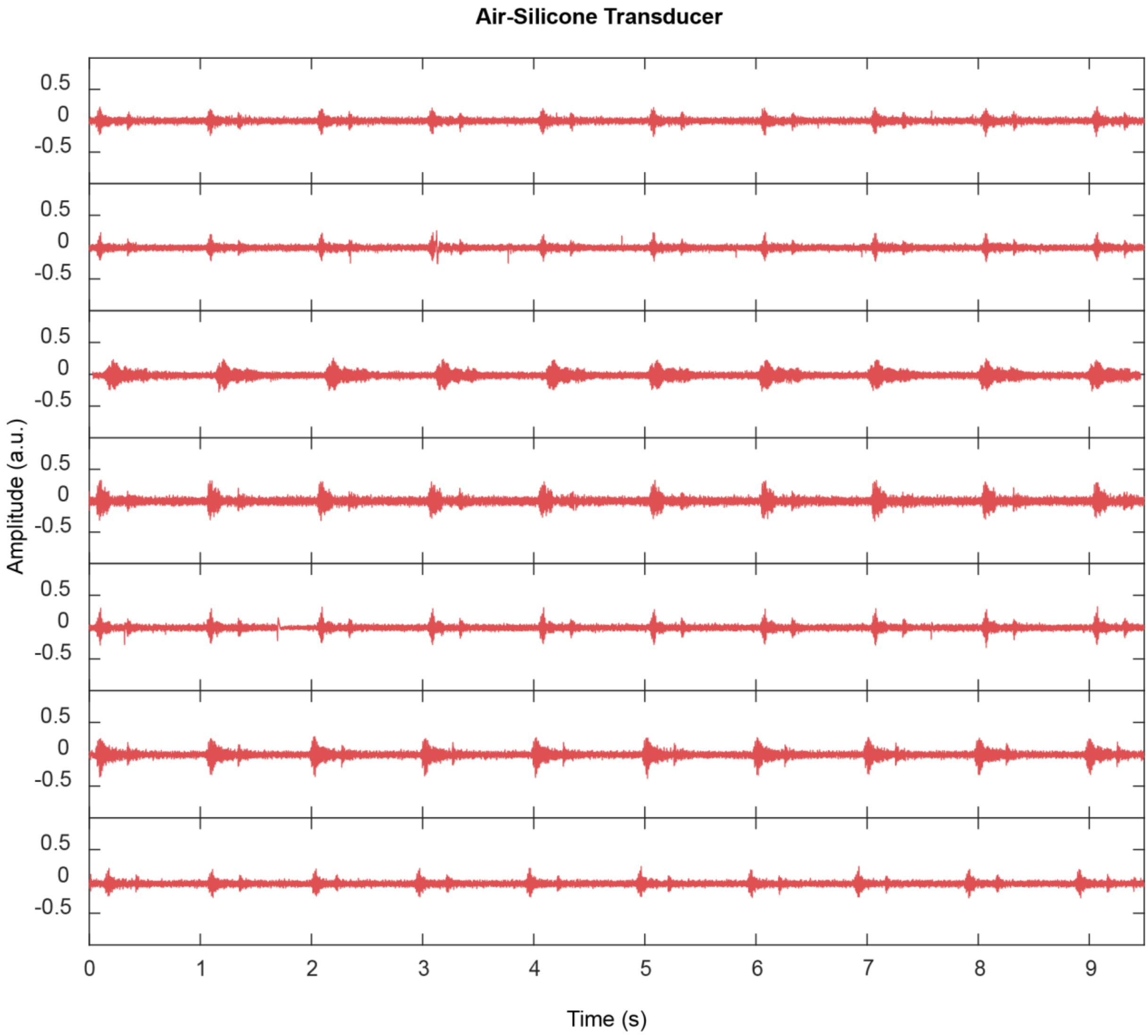

Figure S7. Re-recorded waveforms of the reference recording from seven different air-silicone transducers with a height of 15 mm.

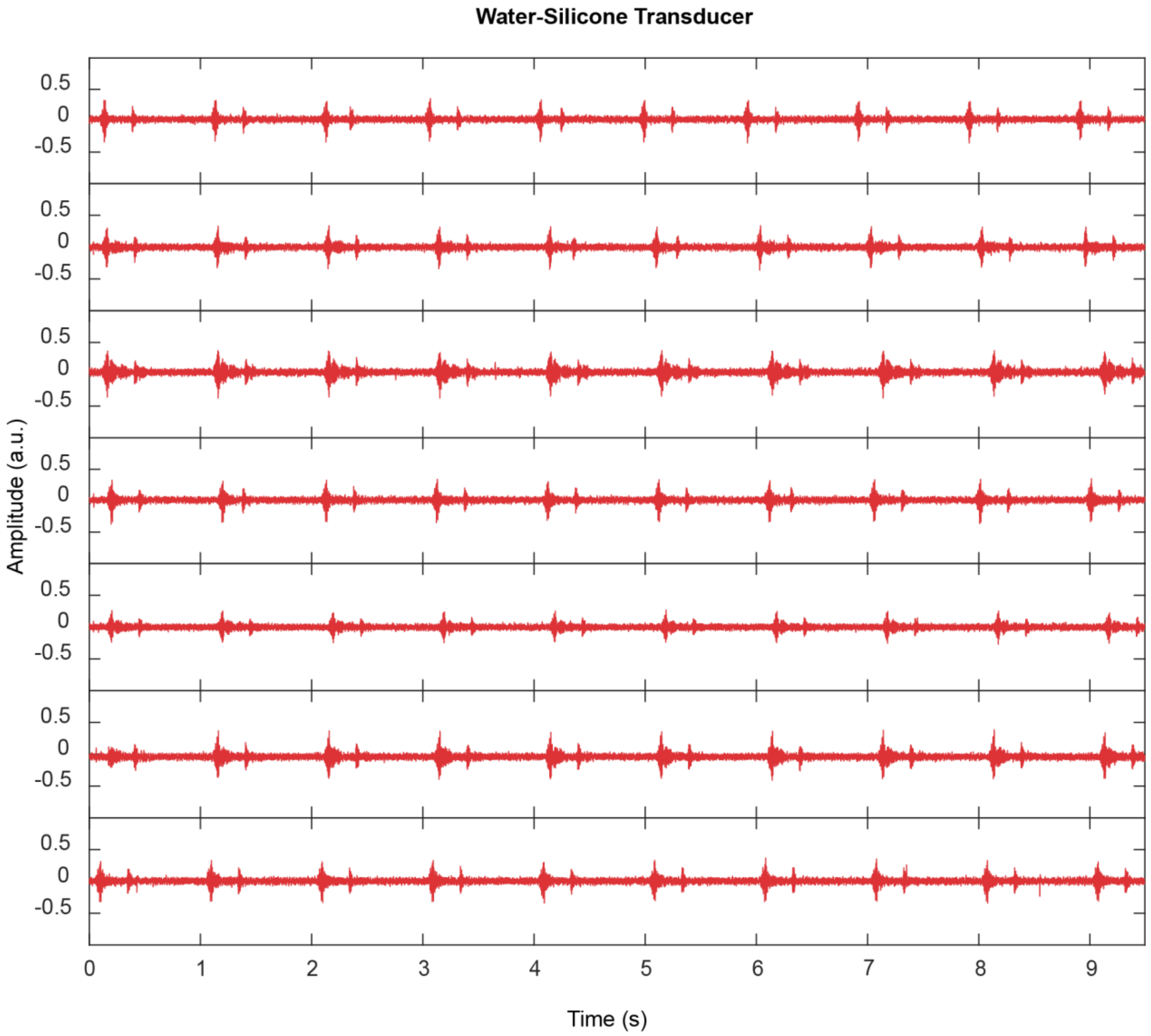

Figure S8. Re-recorded waveforms of the reference recording from seven different water-silicone transducers with a height of 15 mm.

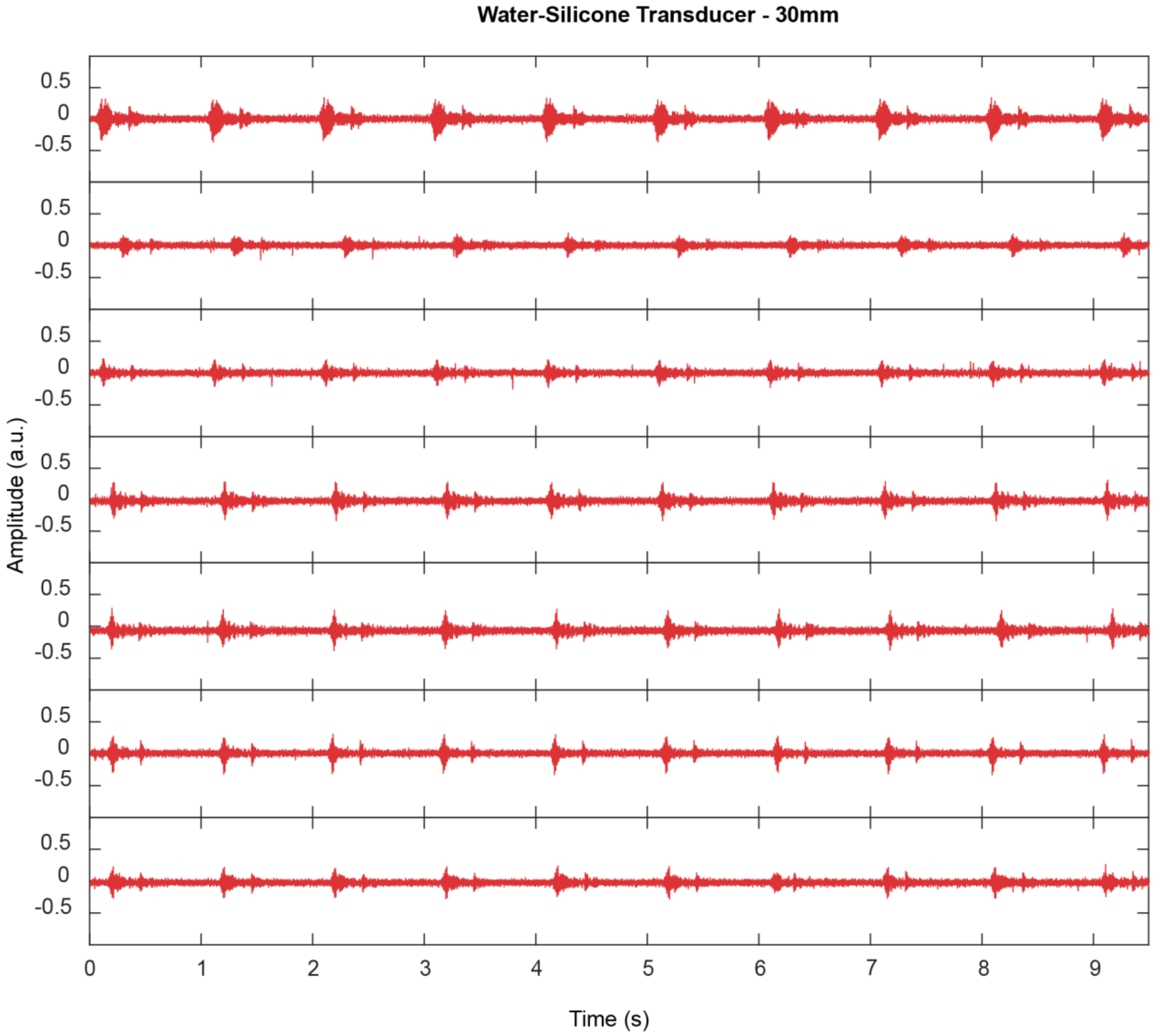

Figure S9. Re-recorded waveforms of the reference recording from seven different water-silicone transducers with a height of 30 mm.

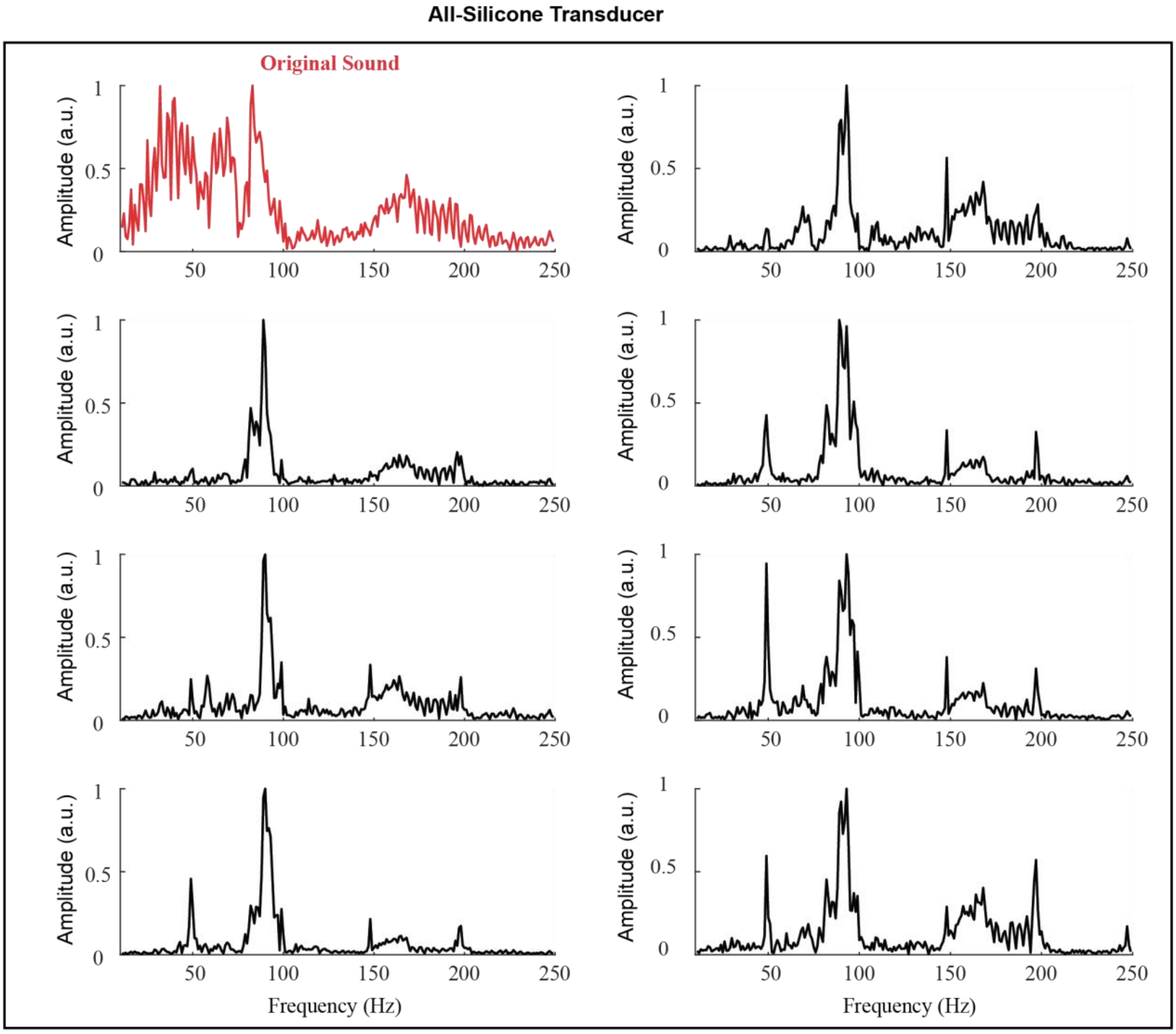

Figure S10. Frequency domain of re-recorded waveforms of the reference recording from seven different all-silicone transducers. Original sound → Reference recording.

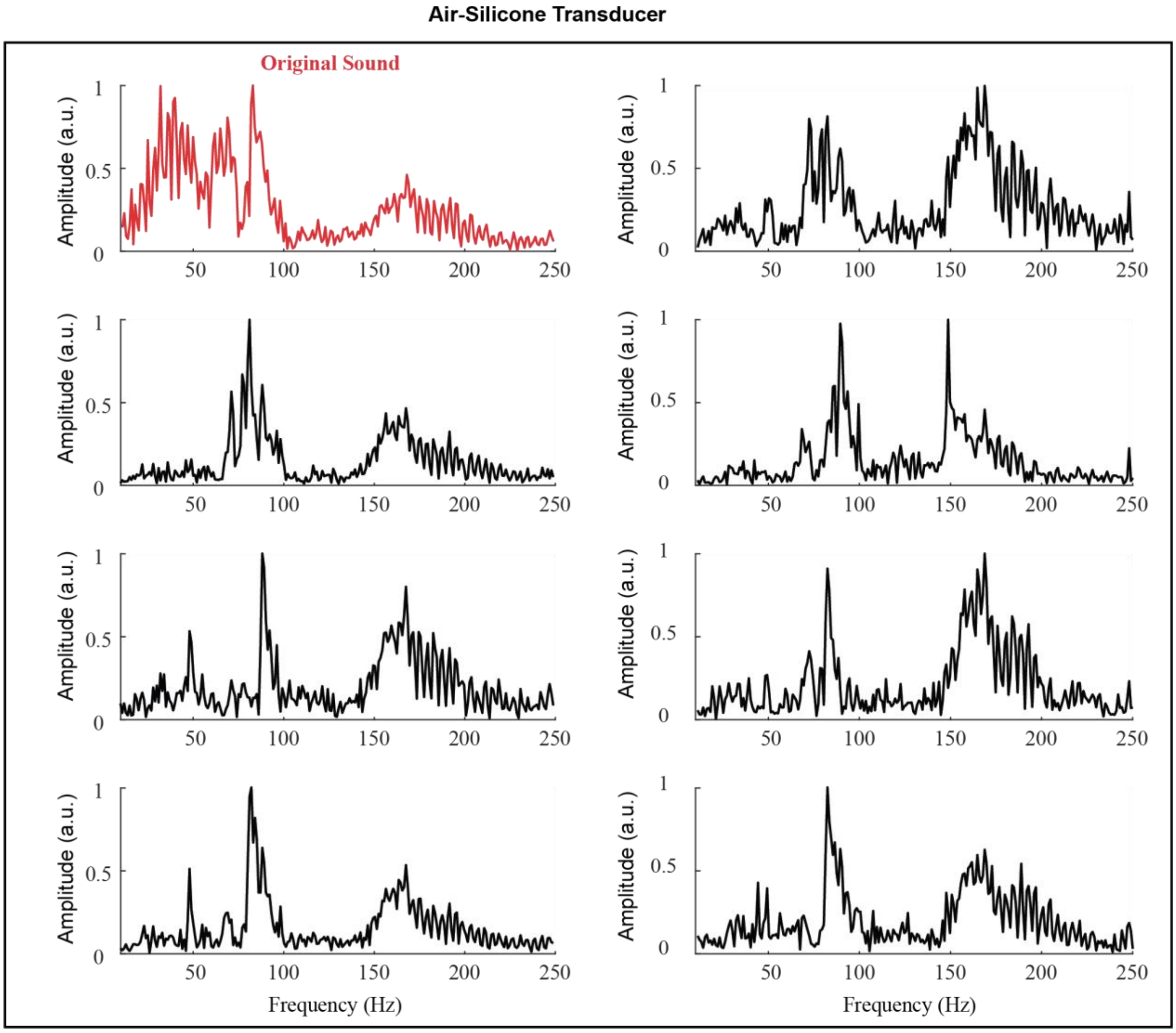

Figure S11. Frequency domain of re-recorded waveforms of the reference recording from seven different air-silicone transducers. Original sound → Reference recording.

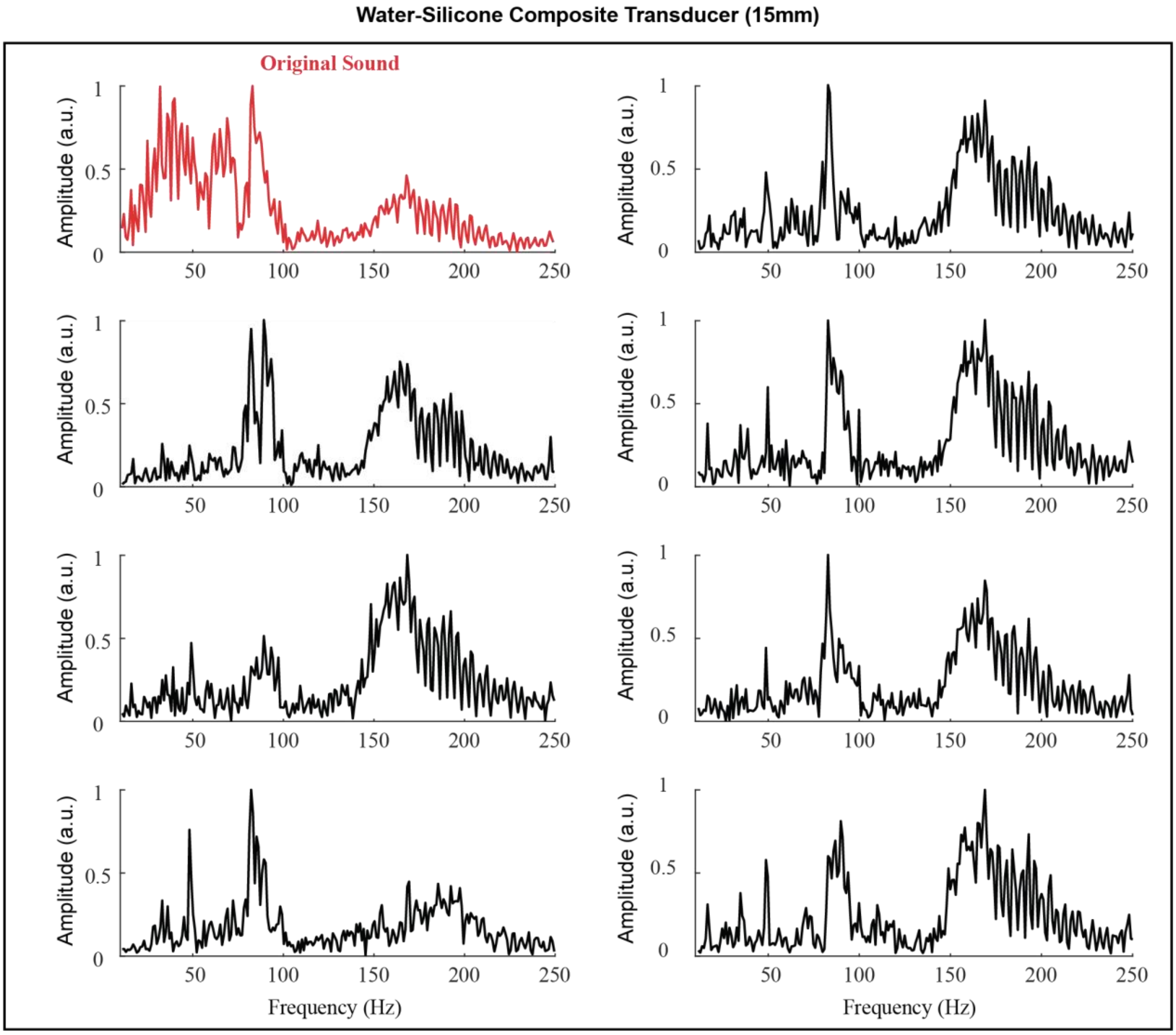

Figure S12. Frequency domain of re-recorded waveforms of the reference recording from seven different 15 mm water-silicone transducers. Original sound → Reference recording.

Water-Silicone Transducer - 30mm

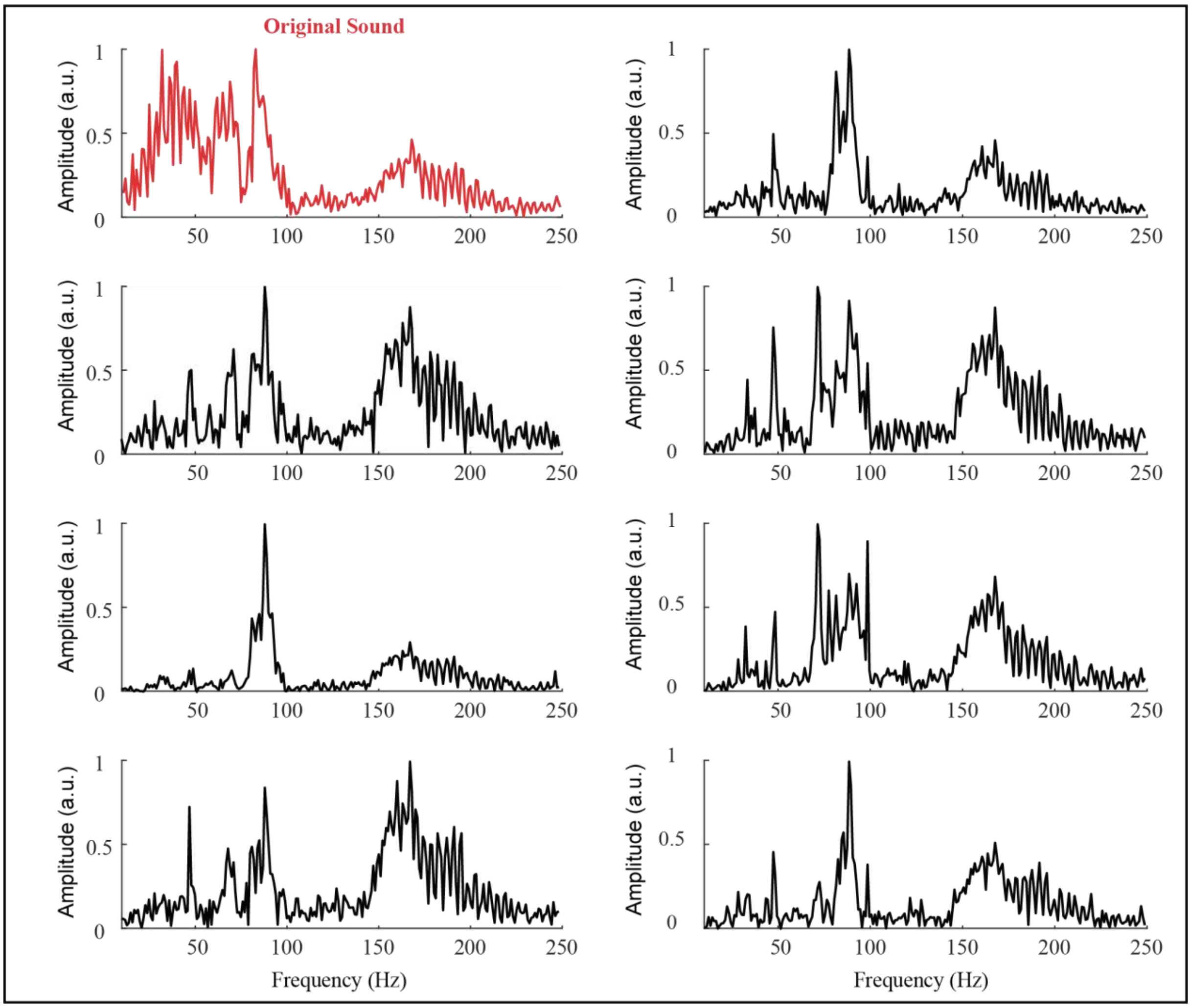

Figure S13. Frequency domain of re-recorded waveforms of the reference recording from seven different 30 mm water-silicone transducers. Original sound → Reference recording.

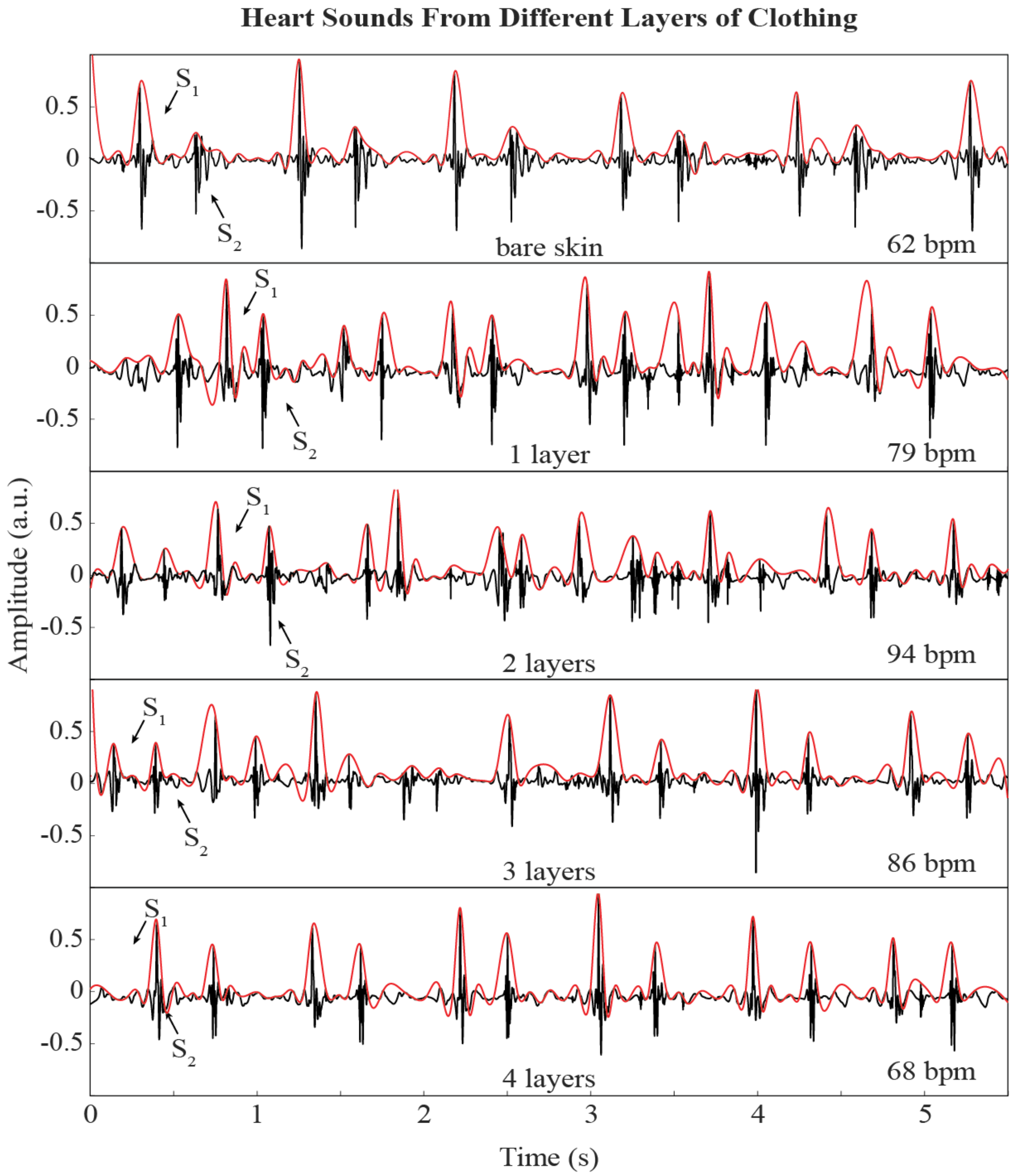

Figure S14. Heart sounds recorded from a human volunteer *vs* layers of clothing. There was no significant impact up to four layers of clothing on the signals acquired. Please note that all signals were filtered with a band-pass filter with passband between 20 - 150 Hz.

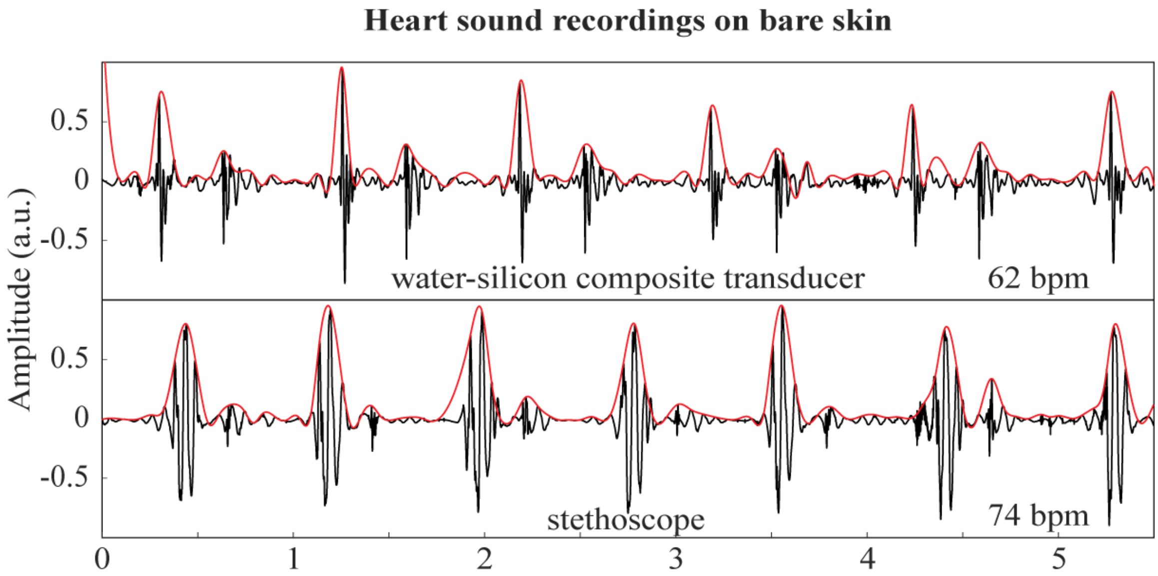

Figure S15. Comparison of heart sound recordings from a bare skin with commercial stethoscope and water-silicone composite transducer.

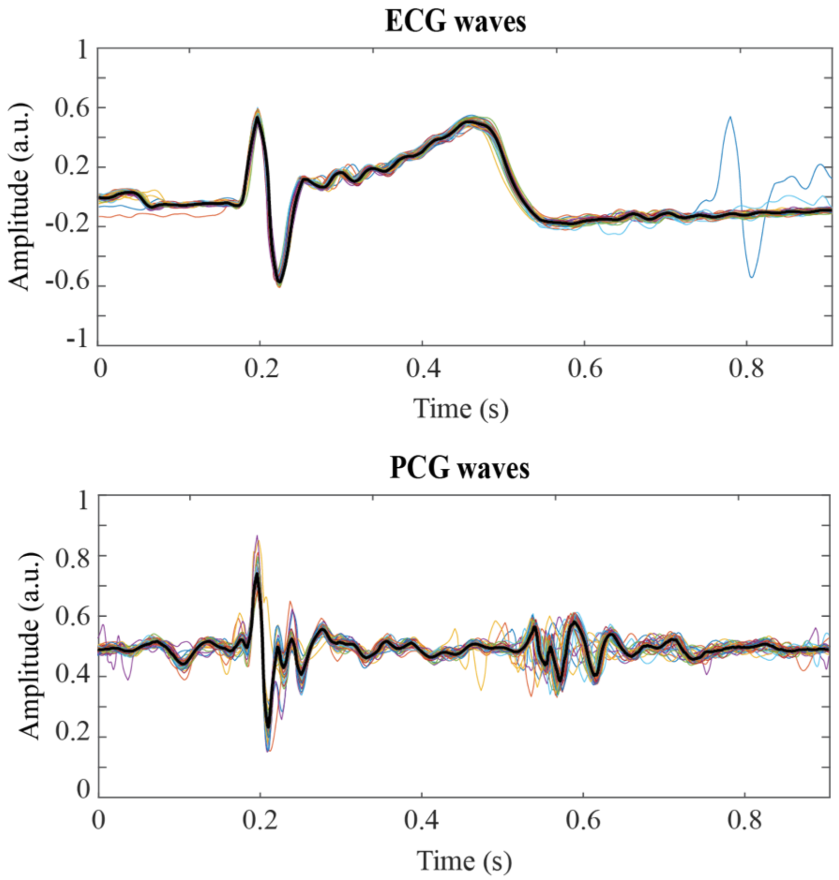

Figure S16. Overlay of each heart cycle recorded by ECG (commercial sensor) and PCG (water-silicone composite transducer) from a human subject. The results shown indicate that the recordings are highly repeatable as the signals from each cycle (illustrated with different colors) are aligned when placed over each other. See **Description SI-D2** below for details of how each cycle is extracted from a recording.

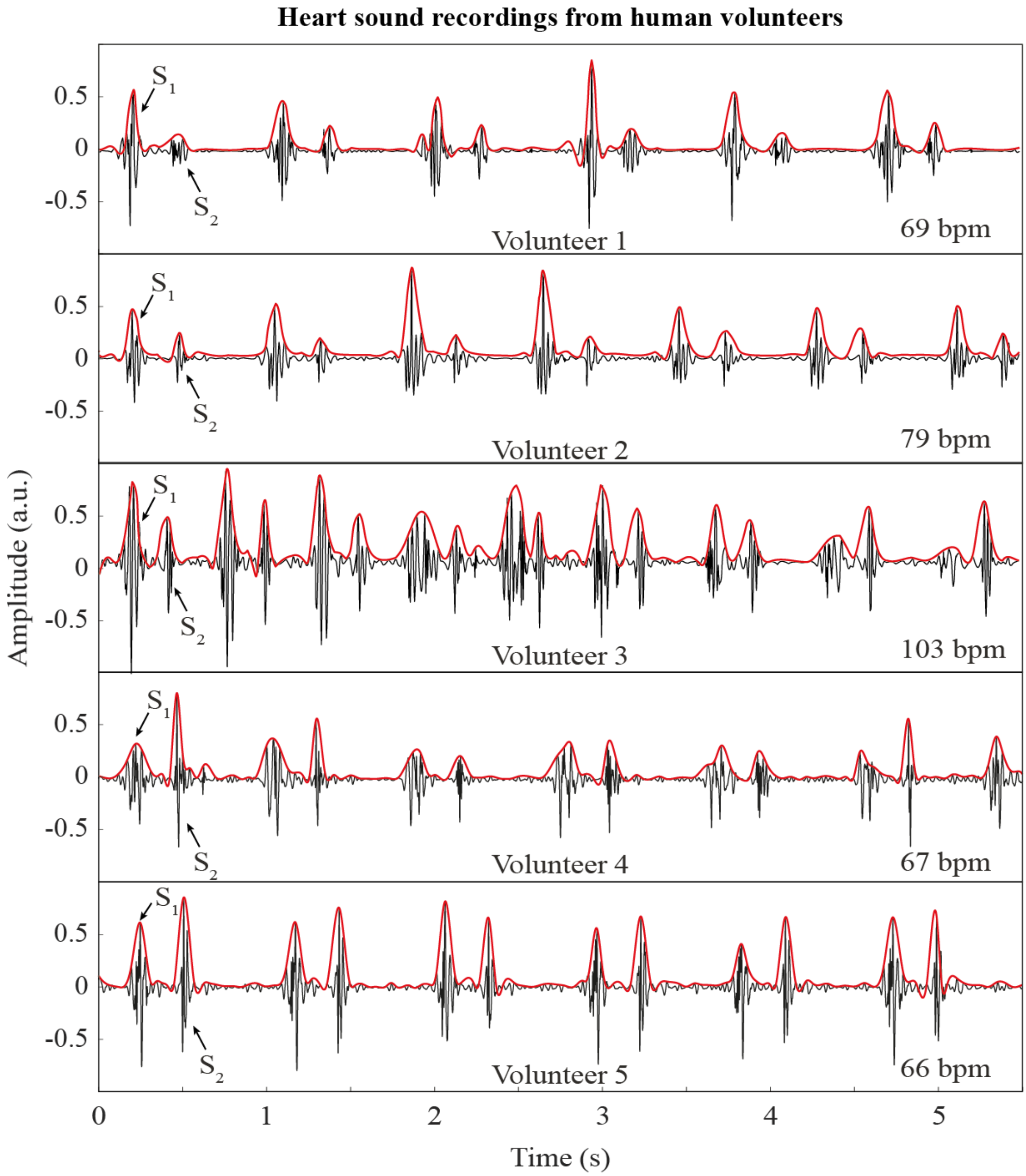

Figure S17. Recordings of heart sounds from human volunteers (n=5) using water-silicone composite transducers. The heart rates are estimated algorithmically. See **Description SI-D3** below for details of how the heart rate is estimated.

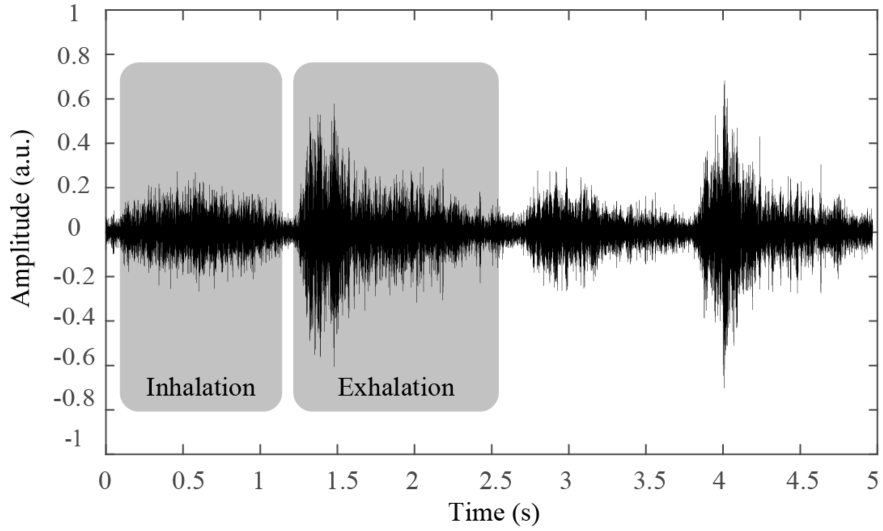

Figure S18. Human breathing sounds collected using a water-silicone composite transducer. The data recorded is filtered between 150 - 1000 Hz to eliminate the heart sounds and other external noise.

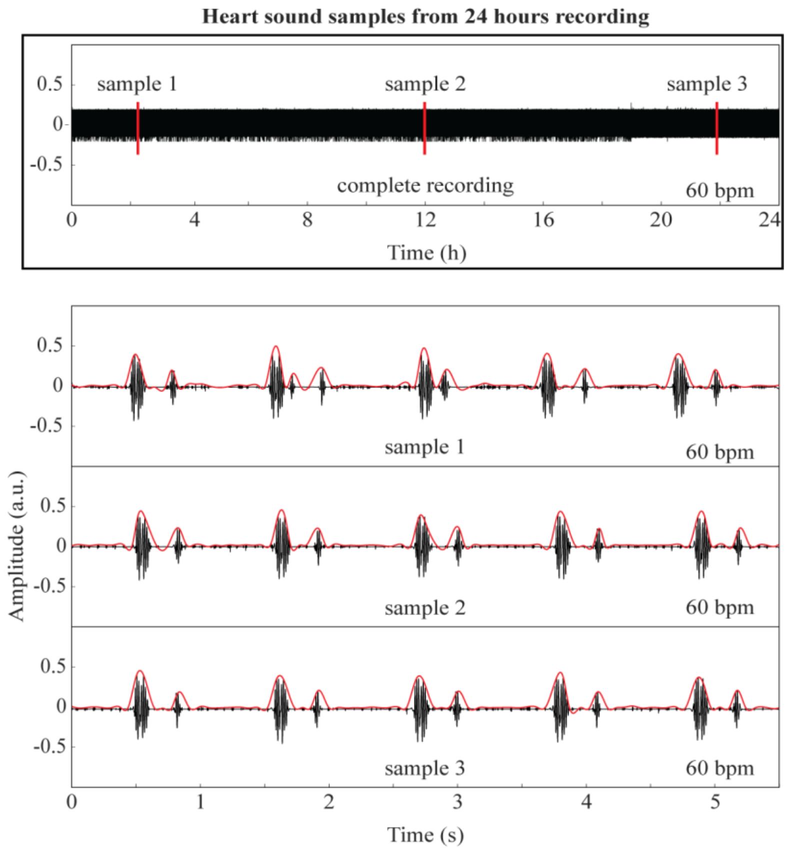

Figure S19. Heart sound samples recorded with water-silicone composite transducer for wearable and unobtrusive continues monitoring of heart sounds for 24 hours.

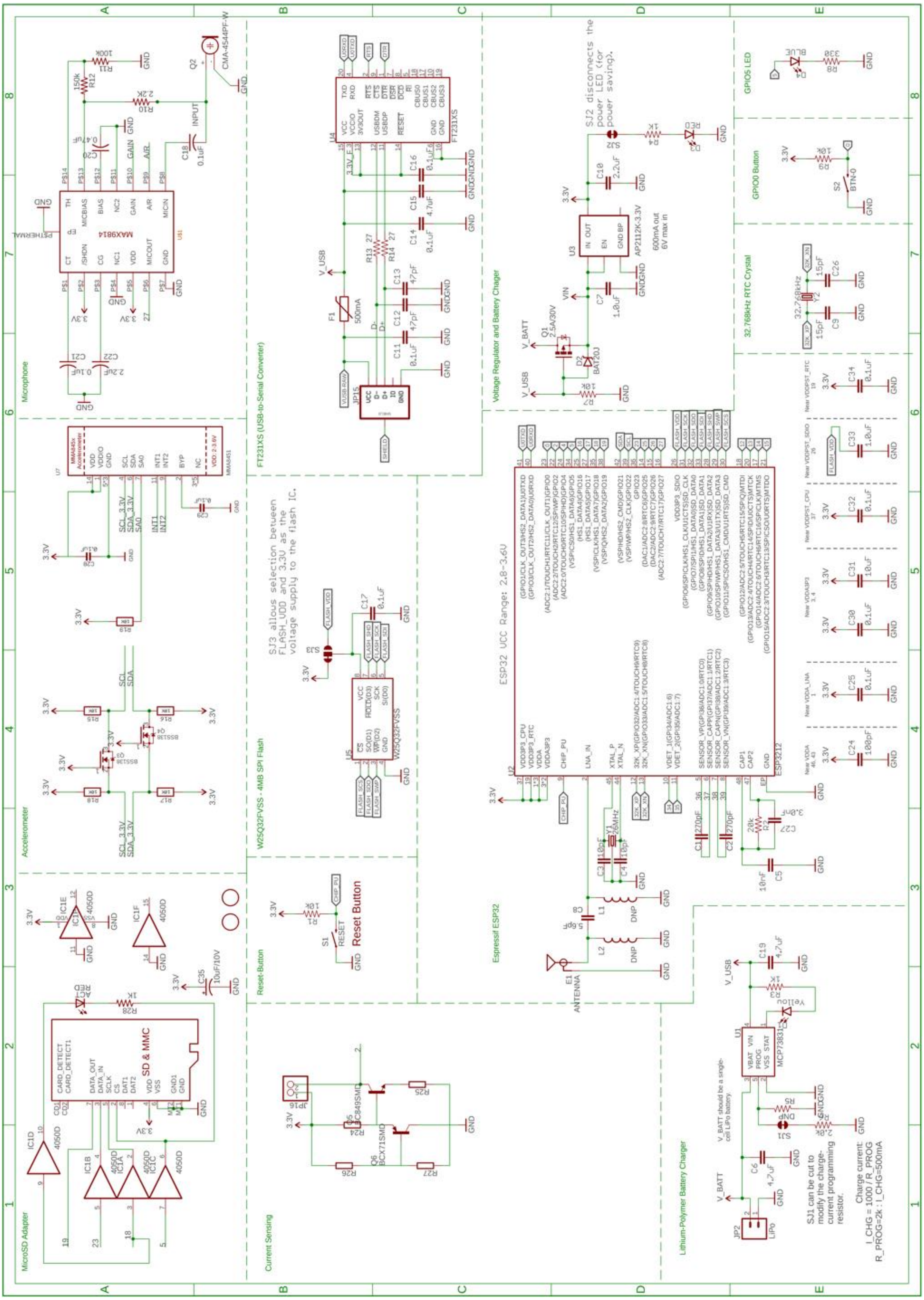

Figure S20. Schematic of the electronics.

2. Detailed description of methods

Description SI-D1

Dynamic Time Warping (DTW)

There are many factors affecting the recordings of an audio signal such as environmental noise, sampling rate, specification of the recording instrument, etc. When calculating the similarity, in other words the error, between two signals, each signal must be perfectly aligned to measure the distance between each point (i.e. recorded sample). This is, in practice, either humanly impossible or impractical as it would take a large amount of time to realign the signals. This is where DTW is used.

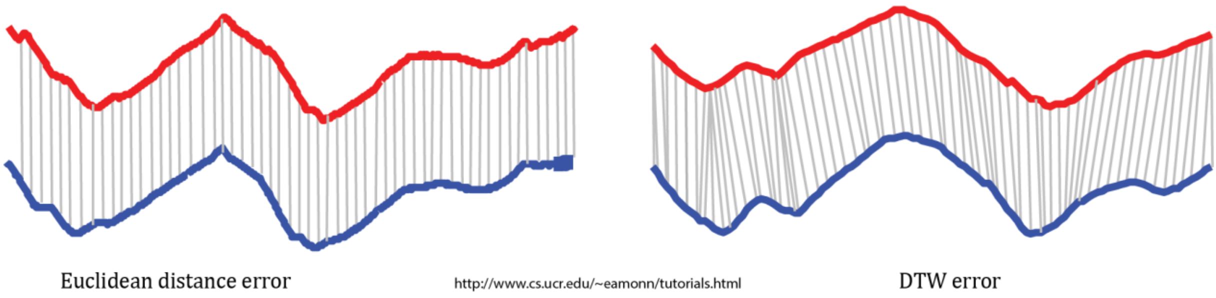

Figure S21. Schematic presentation of the error calculation between two signals using Euclidean distance and DTW methods.

DTW is a robust distance measure to compare non-linear time series signals with different amplitudes and time-lag (or -lead). It is widely used as a similarity measure, especially in biological signal processing such as speech recognition and machine learning. As it can be seen in the above figure, the overall shape of blue and red signals is similar but there are differences in short time frames. DTW method finds the most similar regions by calculating the shortest distance by warping one signal to align to the other. Although this is an old technique, it works exceptionally well, therefore it is often used as a reference measure to compare new methods in the literature. Since we re-recorded a reference heart sound from a speaker with transducers, the overall shape of the recordings would be similar, however they would be misaligned. We used DTW to both align and measure the similarity between each signal to calculate error.

Description SI-D2

Comparison of ECG and PCG Signals

After collecting data, we loaded ECG and PCG signals to the MATLAB workspace and normalized both signals. We interpolated and resampled the ECG signal to match the sampling rate of the PCG signal. The peaks of the ECG signal are detected using the Pan and Tompkins algorithm. This algorithm gives slightly offset peak indices and we have written another algorithm to improve the peak locations as well as ignore peaks of non-ideal ECG patterns. We have modified an algorithm for the measurement of similarities between ECG signals, described by the Springer et. al. (Springer, 2016) In our algorithm, we implemented the following steps for each peak index. A window is created with a length of one second data centered at the peak index. The window is truncated if nonpositive index values exist or index values greater than signal length exist. Using MATLAB's max function, the location of the signal window's max value is found. Then, we check this max (peak) value is unique so that the function has not already found this peak location when looking at another (previous or next) window. If the found peak is unique, we record the location of the peak and take the autocorrelation of the signal window to differentiate good and bad ECG/PCG signals. (Tosanguan, 2009) We used (0.5*sampling frequency) as the cut-off to create a window containing side lobes of the autocorrelation signal. We calculated the area underneath the side lobes and divided by the max value of the autocorrelation window. Once the area/max metric has been calculated for all windows, we normalized the resulting signals. If the metric for a given peak is less than -0.5 or greater than 0.5, the peak is ignored and removed from the output of the function. We used the same peak locations and window on the PCG signal and the max of the PCG window is taken to find the location of the first PCG peak by implementing the same steps above. The difference between the ECG and PCG first peak locations is taken (lag). If lag is positive, that means the ECG's first peak is ahead of the PCG's first peak, so the PCG signal is shifted to the right (PCG variable padded with nan values to shift signal without creating new data). If lag is negative, that means the ECG's first peak is behind the PCG's first peak, so the PCG is shifted to the left (PCG variable padded with nan values to shift signal without creating new data). Peaks of ECG signal and PCG signal are input to our custom function, which will locate PCG peak locations and ignore peaks of non-ideal PCG patterns. Then we added all ECG cycles and PCG cycles separately to find the median waves and compared the similarity (known as Pearson's ratio) between the cycles and the median waves. We obtained 0.9915 and 0.8867 similarity scores between ECG cycles and PCG cycles respectively, which are quite high scores showing that there is low signal to noise ratio in the recordings.

- Springer, D. B.; Brennan, T.; Ntusi, N.; Abdelrahman, H. Y.; Zühlke, L. J.; Mayosi, B. M.; Tarassenko, L.; Clifford, G. D. Automated Signal Quality Assessment of Mobile Phone-Recorded Heart Sound Signals. J. Med. Eng. Technol. 2016, 40 (7–8), 342–355.
- Tosanguan, T. Development of a Sub-Miniature Acoustic Sensor for Wireless Monitoring of Heart Rate, Imperial College London, 2009.

Description SI-D3

Algorithm for the detection of heart rate for PCG recordings

We normalized the waveforms recorded between -1 and 1 and applied a Butterworth bandpass filter in the frequency range of 20 – 150 Hz to eliminate background noise. We applied a wavelet denoising algorithm by passing the following parameters to '*wden*' (wavelet denoising) function in MATLAB:

- Daubechies wavelet (*db2*) with the level of wavelet decomposition as 7,

- Donoho and Johnstone's universal threshold with the DWT (*sqtwolog*),
- rescaling using level-dependent estimates of the noise (*mln*) and
- hard thresholding (*h*).

We have separated the original data in pieces with a length of 40 ms (windowing) and applied the function above to each window for denoising the signal. Next, we applied MATLAB's '*envelope*' detection function to find the S1 and S2 patterns in the waveforms collected. Finally, we used the '*findpeaks'* function in MATLAB to identify the peaks of S1 and S2. We passed in the following parameters into the '*findpeaks'* function:

- 0.5 sec as minimum peak distance between the peaks,
- 0.5 times the maximum value of the sound signal as minimum peak prominence.

After finding the peak locations of S1 and S2, we subtracted two successive peaks from each other to find the distance between subsequent peaks, we labelled small distances (less than 125 ms) as false detection of S1 or S2 locations and eliminated corresponding peaks and only took into account long enough distances (more than 125 ms) as true heart beats. We added all remaining successive peak distances together and took the mean to obtain the heart rate per minute.

3. Videos

Video SI-V1. Fabrication of a water-silicone composite transducer.

Video SI-V2. Stretchability and flexibility of water-silicone composite vs all-silicone diaphragm.

Video S3-V3. Monitoring heart sounds of a human volunteer with a wearable water-silicone composite transducer.