# Supplementary Material

## 1 ESTIMATION OF RESPIRATORY MODULATION

### 1.1 Training and estimation of respiratory modulation using a support vector machine model

A support vector machine (SVM) regression model is used here to estimate the peak-to-peak amplitude of respiration-induced autonomic modulation $a_{resp}$. The SVM $\mathcal{M}_{RR,Resp,AFR}$ was trained using a training dataset $\boldsymbol{\mathcal{X}}^{Sim,Train}$ with the format $\boldsymbol{\mathcal{X}} = [\mathcal{X}_{RR}^{Sim}; \mathcal{X}_{Resp}^{Sim}; \mathcal{X}_{AFR}^{Sim}]$ containing 100 000 parameter sets, as described in Sec. 2.3.2. The SVM was trained with the MATLAB function fitrsvm (MATLAB 2023a) with a Gaussian kernel and normalized predictor data with zero mean and unit variance. The performance of $\mathcal{M}_{RR,Resp,AFR}$ on simulated data was assessed using the testing dataset $\boldsymbol{\mathcal{X}}^{Sim,Test}$ containing 2 million parameter sets, as described in Sec. 2.3.2 of the main manuscript. The performance on $\boldsymbol{\mathcal{X}}^{Sim,Test}$ was assessed using the RMSE, Pearson correlation, and coefficient of determination $R^2$ between the true $a_{resp}$ and estimated $\hat{a}_{resp}$.

### 1.2 Accuracy of support vector machine

The distribution of estimated $\hat{a}_{resp}$ over true $a_{resp}$ for $\mathcal{M}_{RR,Resp,AFR}$ is shown in Fig. S1. Also displayed in Fig. S1 for comparison based on the same data are the corresponding distributions for estimation using a

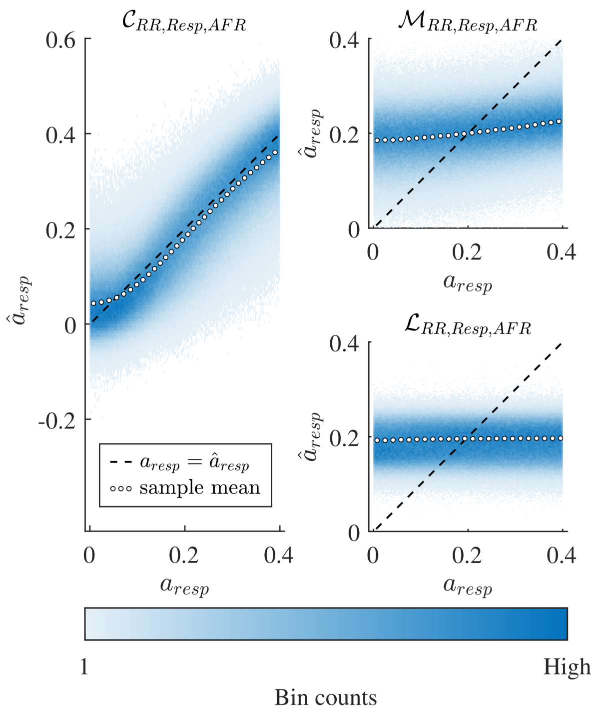


**Figure S1.** Binned scatter plot of estimated $\hat{a}_{resp}$ versus true $a_{resp}$ for the CNN $\mathcal{C}_{RR,Resp,AFR}$, support vector machine $\mathcal{M}_{RR,Resp,AFR}$ and linear regression $\mathcal{L}_{RR,Resp,AFR}$, where all three were based on the same input data $\boldsymbol{\mathcal{X}} = [\mathcal{X}_{RR}^{Sim}; \mathcal{X}_{Resp}^{Sim}; \mathcal{X}_{AFR}^{Sim}]$. The black dotted line shows where $\hat{a}_{resp}$ is equal to $a_{resp}$. The white dotted line shows the sample mean of the $\hat{a}_{resp}$ estimation.

**Table S1.** RMSE, Pearson sample correlation and $R^2$ of $\mathcal{C}_{RR,Resp,AFR}$, support vector machine $\mathcal{M}_{RR,Resp,AFR}$ and linear regression $\mathcal{L}_{RR,Resp,AFR}$ using 1-minute segments.

| | RMSE | Pearson correlation $r$ | $R^2$ |
|---|---|---|---|
| $\mathcal{C}_{RR,Resp,AFR}$ | 0.066 | 0.855 | 0.674 |
| $\mathcal{M}_{RR,Resp,AFR}$ | 0.113 | 0.254 | 0.036 |
| $\mathcal{L}_{RR,Resp,AFR}$ | 0.119 | 0.037 | $-0.068$ |

1-dimensional convolutional neural network $\mathcal{C}_{RR,Resp,AFR}$ and linear regression $\mathcal{L}_{RR,Resp,AFR}$, described in Sec. 2.4.1 and 2.4.2 of the main manuscript. The RMSE, Pearson sample correlation and $R^2$ are listed for $\mathcal{C}_{RR,Resp,AFR}$, $\mathcal{M}_{RR,Resp,AFR}$, and $\mathcal{L}_{RR,Resp,AFR}$ in Table S1. The $\mathcal{L}_{RR,Resp,AFR}$ was unable to estimate $a_{resp}$ (Pearson sample correlation $r = 0.037$); the $\mathcal{M}_{RR,Resp,AFR}$ was able to do some adaptation to the data ($r = 0.254$); however, both $\mathcal{L}_{RR,Resp,AFR}$ and $\mathcal{M}_{RR,Resp,AFR}$ performed clearly worse in estimating $a_{resp}$ than the investigated CNN $\mathcal{C}_{RR,Resp,AFR}$ ($r = 0.855$).