

Explainable Algorithm for Automatic Detection and Quantification of Preload Alterations using Seismocardiography

Emil Korsgaard

`emilk@hst.aau.dk`

Aalborg University

Ahmad Agam

Aalborg University Hospital

Peter Søgaard

Aalborg University Hospital

Rasmus Møgelvang

Rigshospitalet Copenhagen

Charlotte Burup Kristensen

Rigshospitalet Copenhagen

Jørn Wulff Helge

University of Copenhagen

Kasper Sørensen

VentriJect ApS

Johannes Jan Struijk

Aalborg University

Samuel Emil Schmidt

Aalborg University

Article

Keywords:

Posted Date: September 30th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10906309/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: Competing interest reported. P.S., K.S. and S.S. were employed by company Ventriject ApS. E.K. and S.S. are patent application holders of an algorithm used in the current study. S.S., P.S., K.S. and J.J.S. are shareholders in Ventriject ApS. S.S. is shareholder in Acarix AB. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Explainable Algorithm for Automatic Detection and Quantification of Preload Alterations using Seismocardiography

Emil Korsgaard¹, Ahmad Agam^{2,3}, Peter Søgaard^{2,3}, Rasmus Møgelvang⁴, Charlotte Burup Kristensen^{4,5}, Jørn Wulff Helge⁶, Kasper Sørensen⁷, Johannes Jan Struijk¹, and Samuel Emil Schmidt¹

¹ Department of Health Science and Technology, Aalborg University, Aalborg Denmark

² Department of Cardiology, Aalborg University Hospital, Aalborg Denmark

³ Department of Clinical Medicine, Aalborg University, Aalborg Denmark

⁴ Copenhagen University Hospital Rigshospitalet

⁵ Cardiology, Department of Clinical Sciences, Lund University

⁶ Department of Biomedical Sciences, University of Copenhagen, Copenhagen, Denmark

⁷ VentriJect ApS, Denmark

Corresponding Author: Emil Korsgaard, email: emilk@hst.aau.dk

Abstract

Both in heart failure, intensive care, and the perioperative setting there is a need for close monitoring of cardiac hemodynamics such as preload and cardiac output to improve patient outcomes. Monitoring of vital signs is widely used; however, insufficient treatment and high mortality and complication rates persist. Echocardiography is a hemodynamic monitoring method; however, it is operator dependent and does not provide continuous monitoring. Therefore, the aim of this study is to develop and validate a novel algorithm detecting preload alterations using seismocardiography.

Seismocardiograms from 193 subjects from four studies were included. Two studies performed preload modulations decreasing and increasing preload, respectively, while the remaining two studies did not. Beat-to-beat features were extracted from the seismocardiogram. Based on principal component analysis, cluster similarity measures, and linear discriminant analysis, an algorithm predicting probability for preload decrease, no change, and increase was developed.

The algorithm discriminated between decrease in preload and no change in preload with an AUC of 0.807, between decrease and increase in preload with an AUC of 0.909, and between no change and increase in preload with an AUC of 0.854.

In conclusion, an algorithm for precise and explainable detection and quantification of preload alterations was developed and validated.

Introduction

It is estimated that 64 million people suffer from heart failure (HF) worldwide, and in 2018 there were 1.4 million HF related visits to emergency departments only in USA ¹. Predictions for 2030 in USA indicate that frequent hospitalizations will account for more than 70 % of the total direct HF related costs ². Moreover, it has been estimated that there are 313 million surgical procedures yearly worldwide ³. A key commonality between HF and surgical procedures is the requirement for extensive hemodynamic monitoring in order to optimize patient outcomes.

One of the main cornerstones of managing HF is guideline-directed medical therapy (GDMT) that among others make use of hemodynamic monitoring to evaluate response to treatment and assess what treatments to indicate ⁴. Thus monitoring, both in-hospital and remotely, is of great importance within this field. However, the monitoring of vital signs has been shown to be insufficient due to low patient compliance and the fact that the hemodynamic changes occurring in HF manifest late in the vital signs ^{5,6}. Another solution is the invasive CardioMEMS sensor measuring pulmonary artery pressure (PAP), which has provided promising results ^{7,8}. This solution does not require actions from the patients; however, its invasive nature and costs are main drawbacks within this field.

A major problem in surgical procedures are post-operative complications that is a primary cause of death ⁹⁻¹¹. Again, GDMT is used for preventing post operative complications and for ensuring adequate blood flow and oxygen delivery to the tissues ¹². Current monitoring methods in this field also include vital parameters and physical examinations¹³, however, the mortality and post-operative complications persist. Moreover, transthoracic echocardiography (TTE) can be used to evaluate hemodynamic status in perioperative setting and also HF. However, TTE is operator dependent, varying feasibility according to patient habits, requires extensive training, and it does not provide continuous monitoring.

Seismocardiography (SCG) is an easy-to-use and non-invasive technique to measure the local low-frequency movements on the chest wall caused by the mechanical activity of the heart. SCG was introduced by Mounsey in 1957 ¹⁴. Fiducial points in the SCG have been correlated to different physiological cardiac events such as opening and closures of valves, blood flow in ventricular and atrial systole, and time intervals such as ejection time, isovolumetric relaxation time and isovolumetric contraction time ¹⁵⁻¹⁷. In addition, changes in SCG have been related to changes in PAP, myocardial contractility, stroke volume (SV), and preload ¹⁸⁻²⁴.

In summary, SCG has shown its potential to be used to extract central hemodynamic parameters, thus also carrying the potential of being an easy-to-use and cost-effective method for remote and in-hospital monitoring to optimize GDMT. One important

hemodynamic marker reflecting the heart's ability to handle venous return and generate cardiac output (CO) is preload, thus, tracking changes in preload is an important tool in optimizing GDMT. In earlier work, the relation between SCG parameters and preload has been shown²¹⁻²³. However, to scale the use of SCG in the field, it is necessary to develop automated algorithms that identify alterations in preload if it should be used in GDMT in HF and in the perioperative phase. No automated algorithms for detecting changes in preload through the SCG have previously been developed.

Therefore, the aim of this study is to develop an automated algorithm for detecting alterations in preload solely based on features extracted from SCG.

Methods

The algorithm in this study was based on data from four different studies: two performing preload modulations and two studies without intervention as reference data. 42 SCG features were extracted, and based on these features a principal component analysis (PCA) was performed to scale the data to two dimensions. In the 2D feature space, 4 measures of similarity between pre and post intervention were calculated. Based on a linear discriminant analysis (LDA) the probability and direction of preload alteration were calculated.

Study Population

Data from four different experiments were included in the study: Reverse Trendelenburg Experiment (RTE) used in the studies by *Sørensen et. al.*¹⁷, by *Agam et. al.*²¹, and by *Kolind et. al.*²², Saline Infusion Experiment (SIE) used in the study by *Myhr et. al.*²⁵ and *Agam et. al.*²⁴, and two No Intervention Experiments (NIE) used in the studies by *Sørensen et. al.*²⁶ and by *Hansen et. al.*²⁷

Ethical Considerations

The RTE experiment was approved by the Ethical Committee of Northern Jutland (N-20120069)^{17, 21}. SIE experiment was approved by the local ethics committee of the Capital Region of Denmark (H-16029778)^{24, 25}, while the two NIE studies were approved by the ethical committee of Northern Jutland (N-20160034)²⁶ and the local ethics committee of the Capital Region of Denmark (H-17008748)²⁷ respectively. Informed consent was obtained from the participants. All methods were performed in accordance with relevant guidelines and regulations.

Study Protocols and Train/Test Split

The protocol for RTE was to first measure SCG and TTE in supine position. Secondly, the subject was tilted 30 degrees reversed Trendelenburg, where SCG and TTE were measured consecutively. Third, the subject was tilted back to supine position and performed a grip test during which the SCG signal was measured. Finally, the SCG was measured at rest in supine. Grip test was excluded from this study, since the SCG signals were too noisy for meaningful analysis. This resulted in three pairs of data for each subject: *Pre-Tilt* expecting a preload decrease due to lowered venous return, *Tilt-Post* expecting a preload increase due to increased venous return, and *Pre-Post* expecting no preload alterations.

The protocol for SIE was to first measure SCG at rest in supine position. Secondly, the subjects received saline infusion of between 1 liter to 2 liters, depending on each subject's tolerance. This resulted in one pair of data: *Pre-Saline Infusion* expecting a preload increase due to increased venous return. TTE was performed pre and post saline infusion consecutively. The protocol for the two NIEs was just to measure SCG in

supine position at rest. The measurements were split into two equal parts expecting no change in preload. All pairs with expected outcome as preload decrease was labelled -1, no change in preload was labelled 0, and increase in preload was labelled 1. The available data and extracted pairs are illustrated in Figure 1.

In summary, there is one data pair for expected decrease in preload originating from RTE, two data pairs for increase in preload originating from RTE and SIE, and two data pairs for no preload alteration originating from RTE and NIE.

On a subject basis, the data were divided into training (70 %) and test (30 %). Since an algorithm from an earlier study²⁸ is used in preliminary feature extraction, the same data split is used to prevent data leak.

Preprocessing and Initial Feature Extraction

To extract features from the SCG, a beat-to-beat fiducial point extractor named SeismoTracker described in²⁸ was used. This algorithm extracted 11 fiducial points from each beat with sufficient signal quality in the given SCG recording. This algorithm required a forward-backward 3rd order low-pass Butterworth filter with 60 Hz cutoff frequency and a forward-backward 3rd order high-pass Butterworth filter with 1 Hz cutoff frequency.

Based on the 11 extracted fiducial points, 86 features within each beat were extracted. The 11 fiducial points and their relation to events in the cardiac cycle along with the 86 extracted features are shown in Figure 2. The 86 features were time differences between a given fiducial point and all combination of subsequent points, amplitudes of fiducial points, amplitude differences between consecutive fiducial points, and slopes between consecutive points. Thus, the features covered all possible cardiac time intervals and forces affiliated with contraction and relaxation.

The last step in the initial feature extraction was to identify all SCG features that changed significantly in a pooled analysis of the data pairs with an expected change in preload. In the studies by *Agam et. al.*²¹, and by *Kolind et. al.*²², there has been found statistically significant changes in mean SCG parameters pre and post tilt in preload decrease, while it has been shown in the study by *Schmidt et. al.*²³ that there are statistically significant differences in SCG extracted parameters pre and post saline infusion in preload increase.

To extract all features with statistically significant differences, the pre and intervention SCG from the two studies were extracted. In each of the recordings, the 86 SCG features extracted from each beat were averaged, thus, resulting in 86 mean SCG features pre and post intervention in both RTE and SIE. A t-test was used to compare pre and post intervention SCG features for both studies. All SCG features with significant differences and in different directions across the two studies were extracted resulting in

42 SCG features. This process resulted in 42 SCG features that is marked in bold and underlined in Figure 2.

Algorithm Development – From 42 SCG Features to Preload Alteration Detection and Quantification

Based on the training data and the 42 selected SCG features, the algorithm was developed using PCA, extraction of similarity measures, and an LDA model to model the relationship between the similarity measures and preload alterations. The process described in the following sections are illustrated in Figure 3.

Algorithm step 1: PCA to Two-Dimensional SCG Feature Space

The first step of the algorithm development was to reduce the SCG feature dimension to two dimensions using PCA. First and foremost, many of the 42 features contained redundant information, e.g. the time difference between systolic fiducial points and diastolic fiducial points. Secondly, this also simplified the later extraction of similarity measures between two measurements.

The initial 42 selected features were extracted beat-to-beat from each of the training recordings were pooled to one single data set, where it was min-max normalized. Based on the normalized data, a PCA model was fitted to reduce dimensionality to two dimensions in order to extract to SCG principal components (SCG-PCs) reflecting the most variation in the training data set. The feature weights in each SCG-PC were extracted to be able to analyze the results in relation to original SCG features for explainability.

From here on, the beat-to-beat PCA transformed SCG features were analyzed individually for each subject and each data pair. For instance, a subject and a given pair of data, e.g. *Pre-Tilt* for RTE, was processed individually. Next, the same subject from RTE with *Tilt-Post* was processed, and finally the same subject from RTE with *Pre-Post* was processed. For each subject and each pair of data in the SCG-PC space, there were two clusters: one for recording 1 (first cluster) and one for recording 2 (second cluster). Thus, the algorithm was developed for using two SCG recordings as input.

Algorithm step 2: Extract Features in Cluster Analysis

In the two-dimensional SCG-PC feature space, the mean direction vector of preload decrease and preload increase were identified, thus, quantifying the direction of change for a preload decrease and increase, respectively. The subjects with pairs of data resulting in expected increase in preload and decrease in preload were extracted, i.e. NIE and *Pre-Post* for RTE were excluded for this analysis.

For each subject and each pair of data the unit vector between the centroids of SCG-PC cluster 1 and SCG-PC cluster 2 were calculated, and this vector was labelled according to expected outcome of the given data pair. This provided a unit vector for both preload

decrease and increase in SCG-PC space for the training data. The mean unit vector for each label was extracted, providing a mean unit vector in SCG-PC space representing preload decrease and preload increase direction.

In this step, the training data were processed following the same procedure as in the previous step, however, also data with no preload alteration expected were included. Then again, for each subject and each pair of data in the SCG-PC space, there was the first cluster and the second cluster.

First the Euclidean distance between the cluster centroids was calculated as a measure of potential change between the two measurements. Secondly, the silhouette score was calculated between the two clusters. The silhouette score measured the separation between the two clusters by comparing mean intra-cluster distance and mean inter-cluster distance. The silhouette score was calculated as presented in Equation 1.

$$S_{score} = \frac{b - a}{\max(a, b)}$$

Equation 1

where a is mean intra cluster distance and b is the mean inter cluster distance. The score resulted in a value between -1 and 1, where -1 indicated no separation between clusters, and 1 indicated perfect separation between clusters. Therefore, if Silhouette score was close to 1, it indicated a change between the two recordings.

Another measure for cluster separation was KMeans AUC. This was calculated by fitting an unsupervised KMeans model to identify two clusters. Then the AUC between the KMeans fitted clusters and SCG-PC cluster 1 and SCG-PC cluster 2 was calculated as an additional measure of class separation. If the KMeans model successfully identify two clusters similar to the clusters of the two recordings, it would result in AUC close to 1 and also indicate change between the two recordings.

To add the direction of change in order to identify decrease and increase in preload, the mean unit vector for these preload alterations and the cosine similarity measure were used. The cosine similarity is calculated as shown in

$$CoSim_{score}(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

Equation 2

where the numerator is the dot product between the two vectors, and the denominator is the product of the magnitudes. This score was also between -1 and 1, where -1 indicated opposite directions, 0 indicated orthogonality, and 1 indicated same directions. The vector representing the direction between SCG-PC cluster 1 and SCG-

PC cluster 2 was calculated as the unit vector between their centroids. Then the cosine similarity was calculated to both of the mean direction unit vectors.

Thus, five features representing the similarity between the two measurements were extracted. For each pair, the similarity measures were extracted and labelled according to expected preload alteration outcome according to the logic presented in Figure 1 resulting in three classes and five features. The distribution of the similarity features in training and test set are illustrated in Supplementary Materials Figure S1.

Algorithm step 3: LDA to Model the Relationship Between Similarity Measures and Preload Alterations

To model the relationship between the similarity measures and the expected preload alteration, an LDA was fitted to the similarity measures based on the labels. This LDA model created decision boundaries based on the features resulting in a probability of a decrease, no change, and an increase in preload for a given pair of measurements. This also marks the end step of the preload alteration detection algorithm

Evaluation of Preload Alteration Detection Algorithm

The preload alteration detection algorithm was evaluated based on the test data and their respective labels according to experiment and pair of data. Each subject and each pair of data was input to the algorithm and a preload alteration probability score for preload decrease, no change in preload, and preload increase were output by the algorithm. Based on this, and the corresponding labels, a one vs. one ROC curve was made between each pair of expected outcomes. Based on this, a ROC-AUC was calculated.

Moreover, a stacked bar plot was made to analyze the mean probability for each outcome across each label and experiment. Thus, each stacked bar represented the probabilities for each preload alteration outcome: preload decrease, no change in preload, and preload increase in the given data set.

Additionally, in expected decrease in preload for RTE and expected increase in preload for SIE, TTE measures were obtained. It is noteworthy that there are only TTE measures from RTE and SIE in the indicated interventions. TTE was not obtained in the other interventions and studies. The difference in HR, SV, and CO for the data pairs is also calculated, since these also are a measure of how much preload changed in these two pairs of data. To investigate if there was a correlation between the preload alteration probability score and the change in SV, the probability scores were converted to a continuous score by subtracting the probability for increase in preload from the probability for decrease in preload. Thus, the continuous score is close to 1 when the probability of increase in preload is high, while the score is close to -1 when the probability of decrease in preload is high. A scatter plot with the continuous score on x-

axis and difference in SV on the y-axis were made. The Pearson correlation coefficient between the score and SV change was calculated.

Results

193 subjects were included. 5 subjects were excluded from the study due to withdrawals or SCG signal quality insufficient for analysis resulting in 188 subjects included in algorithm development and validation. Baseline characteristics on the included subjects are shown in Table 1 for both training and test data. For RTE, the mean difference in SV in intervention expecting preload decrease is -8.2 mL, while it is 17.1 mL for SIE expecting a preload increase in test data.

SCG-PC1 represent 45.2 % of explained variance in the dataset, while SCG-PC2 represent 20.8 %. The 20 original SCG features with the highest absolute weight on the SCG-PC components and the mean unit direction vectors of preload decrease and preload increase are illustrated in Figure 4 a) and Figure 4 b), respectively. The time differences between fiducial points in the systolic complex and the fiducial points in the diastolic complex result in the highest weight on SCG-PC1 in the positive direction. For SCG-PC2, the difference in amplitude from Dd-Ed and the slope from Cd-Dd have the highest weights in positive direction. The time differences from fiducial points Es and Fs to Ks and the Ed amplitude have high feature weight on SCG-PC2 in negative direction.

The one vs. one ROC-AUC is illustrated in Figure 5. The obtained ROC-AUC between expected decrease and no change in preload was 0.807, between expected increase and decrease in preload was 0.909, and between no change vs increase in preload was 0.854.

The stacked bar plot is shown in Figure 6 illustrating the predicted preload alteration probabilities for each possible outcome for all pairs of data across the three studies. The mean predicted probability for a preload decrease in RTE when expecting a preload decrease was 0.670, while the predicted probability was 0.226 and 0.103 for predicted no change and preload increase, respectively.

The mean predicted probability for RTE when not expecting a change in preload is 0.226, while the predicted probability is 0.113 and 0.660 for preload decrease, no preload change, and preload increase, respectively. For the NIE data when expecting no preload alterations, the predicted probability was 0.145, 0.810, and 0.046 for preload decrease, no preload change, and preload increase, respectively. For expected preload increase for the RTE study, the mean predicted probabilities were 0.648, 0.215, and 0.137 for preload decrease, no preload change, and preload increase, respectively. For the SIE in expected preload increase the predicted probabilities were 0.668, 0.285, and 0.027 for preload decrease, no preload change, and preload increase, respectively.

The continuous preload alteration score based on the predicted probabilities from the algorithm and the change in SV result in a Pearson correlation coefficient of 0.630 and the scatter plot is illustrated in Figure 7.

Discussion

By combining simple signal processing methods in the form of PCA and LDA with a cluster-based similarity measures, an explainable model predicting probabilities for preload decrease, no preload change, and preload increase has been developed. The algorithm in the current work is the first to automatically track changes in preload based on automatically beat-to-beat extracted SCG features.

Current hemodynamic monitoring in HF patients and the perioperative setting is not sufficient and does not provide the necessary clinical applicability to adjust treatment and improve outcome for the patients^{5, 6, 11, 29}. Within both HF and in perioperative patients preload alterations will occur, and it is an important parameter for the heart's ability to produce the required CO. Thus, since the developed algorithm can track preload alterations with AUCs above 0.8, it is a step towards continuous monitoring of central hemodynamic parameter that possibly could be used to guide GDMT through SCG. Additionally, the sensor required for obtaining SCG signals is very small and lightweight and thus convenient for patients to wear both in-hospital and remote extending its application area.

This carries the possibility for using it as constant continuous monitoring in HF patients in their daily lives as well as in patients undergoing surgical procedures that can wear the sensor until discharge or stabilization. However, the minimal recording duration for obtaining a useful SCG signal is down to 30 seconds, so it will also be possible to use such system for samples and spot checks whenever that is found feasible.

An advantage of the developed algorithm is its explainability. The SCG-PC features obtained from the PCA can be tracked to the original features through the feature weights. Moreover, the features with the highest weights are also consistent with earlier findings based on the same data²¹⁻²³. A larger value of SCG-PC1 is affiliated with an increase in preload, and based on the feature weights this means a prolonged time between systolic and diastolic complex according to an increased ejection time due to increased venous return. This is consistent with the findings by *Schmidt et. al.*²³.

In addition, the time from fiducial points Es and Fs to fiducial point Ks had high negative weight on SCG-PC2, indicating that a decrease in these time intervals is affiliated with a preload increase. This is due to the decreased contraction time required to reach the peak systolic outflow as venous return increases, which is consistent with the findings by *Kolind et. al.*²². Also, the diastolic amplitude difference between fiducial points Dd and Ed increases as preload increases, which might be due to increased forces required for ventricular relaxation due to higher end systolic volume. In summary, the feature weights and identified directions of preload decrease and increase in the SCG-PC feature space align with the expected physiological changes occurring in preload modulations, which strengthens its potential use in clinical practice.

Based on the stacked bar plots and the obtained AUCs, the algorithm was challenged when predicting data with no expected change in preload in RTE. Often, the model predicted preload increase on this data. Since the predictions on the NIE for no expected preload alterations resulted in high mean probability for prediction of no change, it might be caused by the data acquisition protocol in RTE. Before the post measurement has been performed, the subjects performed a grip test, which potentially resulted in an actual increase in preload for these subjects. Moreover, the subjects were tilted prior to this measurement, and the subject's cardiovascular system might still be compensating for this. Both of these reasons could indicate that the expected no change in preload for the RTE actually could be a preload increase due to experimental protocol. Additionally, the changes in CO for the RTE for expected decrease in preload are small compared to SIE for expected increase in preload, indicating that the actual preload response is higher in the SIE data. This could also explain why the AUC was lowest when differentiating between expected decrease in preload vs no change in preload.

The Pearson correlation of 0.63 between the change in SV and the continuous preload alteration score extracted from the algorithm indicate a weak correlation between the change score and SV changes. Multiple reasons for this exist. Firstly, the TTE extracted SV is not measured simultaneously to the SCG features, low number of subjects, and the features were not extracted with the sole purpose to estimate SV. However, in earlier studies a strong correlation between SV and SCG extracted features has been found ^{18, 30, 31}. This supports the use of SCG in hemodynamic monitoring.

Study Limitations

The number of subjects in the data pairs with expected decrease in preload is relatively low, while also the use of reverse Trendelenburg in healthy subjects might not cause high preload alterations due to compensatory factors. Therefore, it would be relevant to perform alternative preload modulations provoking a more extensive preload decrease than in RTE. However, it is also a strength that the algorithm's performance is not as good as in the SIE study in the low degree reverse Trendelenburg if it should be used in monitoring setting, since similar changes would also occur in remote and in-hospital monitoring due to patient positioning changes. In these cases, it is not relevant that the algorithm indicates a significant preload change. Moreover, only some of the subjects in SIE had CVD, however, the subjects in NIE and RTE were healthy. It is relevant to include more subjects with CVD to also prove feasibility of the algorithm in relevant CVD groups for use in perioperative phase and HF monitoring.

In addition, this is an exploratory feasibility study of an algorithm for detecting changes in preload. There is still the need for more extensive trials with CVD patients to be able to correlate the preload change predictions to specific outcomes to obtain the ultimate goal: the possibility of using the algorithm in clinical practice to e.g. use in GDMT.

Conclusion

An explainable algorithm for automatic detection and quantification of preload alterations using simple PCA, cluster similarity measures, and LDA has been developed and tested. With further validations, the algorithm could potentially be used in monitoring HF patients and in the perioperative setting.

References

1. Tsao, C. W. *et al.* Heart Disease and Stroke Statistics-2022 Update: A Report From the American Heart Association. *Circulation* **145**, e153–e639 (2022).
2. Savarese, G. *et al.* Global burden of heart failure: a comprehensive and updated review of epidemiology. *Cardiovasc Res* **118**, 3272–3287 (2023).
3. Meara, J. G. *et al.* Global Surgery 2030: evidence and solutions for achieving health, welfare, and economic development. *The Lancet* **386**, 569–624 (2015).
4. Patel, J. *et al.* Guideline-Directed Medical Therapy for the Treatment of Heart Failure with Reduced Ejection Fraction. *Drugs* **83**, 747–759 (2023).
5. Mohebali, D. & Kittleson, M. M. Remote monitoring in heart failure: current and emerging technologies in the context of the pandemic. *Heart* **107**, 366–372 (2021).
6. Bekfani, T. *et al.* A current and future outlook on upcoming technologies in remote monitoring of patients with heart failure. *Eur J Heart Fail* **23**, 175–185 (2021).
7. Adamson, P. B. *et al.* CHAMPION trial rationale and design: the long-term safety and clinical efficacy of a wireless pulmonary artery pressure monitoring system. *J Card Fail* **17**, 3–10 (2011).
8. Abraham, W. T. *et al.* Sustained efficacy of pulmonary artery pressure to guide adjustment of chronic heart failure therapy: complete follow-up results from the CHAMPION randomised trial. *Lancet* **387**, 453–461 (2016).
9. Pearse, R. M. *et al.* Identification and characterisation of the high-risk surgical population in the United Kingdom. *Crit Care* **10**, R81 (2006).
10. Pearse, R. M. *et al.* Mortality after surgery in Europe: a 7 day cohort study. *The Lancet* **380**, 1059–1065 (2012).
11. Khuri, S. F. *et al.* Determinants of long-term survival after major surgery and the adverse effect of postoperative complications. *Ann Surg* **242**, 326–343 (2005).
12. Saugel, B. *et al.* Intraoperative haemodynamic monitoring and management of adults having non-cardiac surgery: Guidelines of the German Society of Anaesthesiology and Intensive Care Medicine in collaboration with the German Association of the Scientific Medical Societies. *J Clin Monit Comput* **38**, 945–959 (2024).
13. Pinsky, M. R. Hemodynamic evaluation and monitoring in the ICU. *Chest* **132**, 2020–2029 (2007).
14. Mounsey, P. Præcordial Ballistocardiography. *Heart* **19**, 259–271 (1957).

15. Crow, R. S., Hannan, P., Jacobs, D., Hedquist, L. & Salerno, D. M. Relationship between Seismocardiogram and Echocardiogram for Events in the Cardiac Cycle. *American Journal of Noninvasive Cardiology* **8**, 39–46 (2017).
16. Salerno, D. M. & Zanetti, J. Seismocardiography for monitoring changes in left ventricular function during ischemia. *Chest* **100**, 991–993 (1991).
17. Sørensen, K., Schmidt, S. E., Jensen, A. S., Søgaard, P. & Struijk, J. J. Definition of Fiducial Points in the Normal Seismocardiogram. *Sci Rep* **8**, 15455 (2018).
18. Tavakolian, K. *et al.* Myocardial contractility: a seismocardiography approach. *Annu Int Conf IEEE Eng Med Biol Soc* **2012**, 3801–3804 (2012).
19. Lee, J. *et al.* Novel blood pressure and pulse pressure estimation based on pulse transit time and stroke volume approximation. *Biomed Eng Online* **17**, 81 (2018).
20. Tavakolian, K., Dumont, G. A., Houlton, G. & Blaber, A. P. Precordial vibrations provide noninvasive detection of early-stage hemorrhage. *Shock* **41**, 91–96 (2014).
21. Agam, A. *et al.* Correlation between diastolic seismocardiography variables and echocardiography variables. *Eur Heart J Digit Health* **3**, 465–472 (2022).
22. Kolind, C. M. *et al.* Seismocardiography and echocardiography: the correlation in the systolic complex. *Biomed Phys Eng Express* **10** (2024).
23. Schmidt, S. E., Kristensen, C. B., Soerensen, K., Soegaard, P. & Mogelvang, R. Quantifying preload alterations using a sensitive chest-mounted accelerometer. *European Heart Journal* **42**, ehab724.3044 (2021).
24. Agam, A. *et al.* Evaluation of seismocardiography in detecting pre-load changes and cardiovascular disease: a comparative study with transthoracic echocardiography. *European Heart Journal - Digital Health*, ztaf037 (2025).
25. Myhr, K. A. *et al.* Accuracy and sensitivity of three-dimensional echocardiography to detect changes in right ventricular volumes: comparison study with cardiac magnetic resonance. *Int J Cardiovasc Imaging* **37**, 493–502 (2021).
26. Sørensen, K. *et al.* A Clinical Method for Estimation of VO₂max Using Seismocardiography. *Int J Sports Med* **41**, 661–668 (2020).
27. Hansen, M. T. *et al.* *Determination of Maximal Oxygen Uptake Using Seismocardiography at Rest* Ser. 48, September 1, 2021).
28. Korsgaard, E. *et al.* Deep learning-based beat-to-beat delineation of heart sounds and fiducial points in seismocardiography. *Front. Digit. Health* **7** (2025).
29. Dharap, S. B., Barbaniya, P. & Navgale, S. Incidence and Risk Factors of Postoperative Complications in General Surgery Patients. *Cureus* **14**, e30975.

30. Tavakolian, K., Blaber, A. P., Ngai, B. & Kaminska, B. *Estimation of hemodynamic parameters from seismocardiogram*, September 1, 2010).

31. Semiz, B. *et al.* Non-Invasive Wearable Patch Utilizing Seismocardiography for Peri-Operative Use in Surgical Patients. *IEEE J Biomed Health Inform* **25**, 1572–1582 (2021).

Author Contributions

E.K.: Conceptualization, methodology, software, validation, formal analysis, writing original draft, visualization. A.A: Conceptualization, formal analysis, writing – review and editing. P.S.: Conceptualization, formal analysis, writing – review and editing, supervision, R.M: Data acquisition, writing – review and editing. C.B.K: Data acquisition, writing – review and editing, J.W.H.: Data acquisition, writing – review and editing. K.S: Conceptualization, methodology, formal analysis, data acquisition, writing – review and editing. J.J.S: Supervision, writing – review and editing. S.E.S: Conceptualization, methodology, validation, formal analysis, writing – review and editing, supervision.

Data availability statement

The data supporting the findings of this study are not publicly available due to patient privacy and ethical restrictions but are available from the corresponding author upon reasonable request, subject to approval by the relevant institutional review boards and data protection regulations.

Additional Information

P.S., K.S. and S.S. were employed by company Ventriject ApS. E.K. and S.S. are patent application holders of an algorithm used in the current study. S.S., P.S., K.S. and J.J.S. are shareholders in Ventriject ApS. S.S. is shareholder in Acarix AB.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

E.K. and A.A. received salary from the Novo Nordisk Distinguished Innovator Grant, an independent grant program. No other funding was involved in project.

Figures

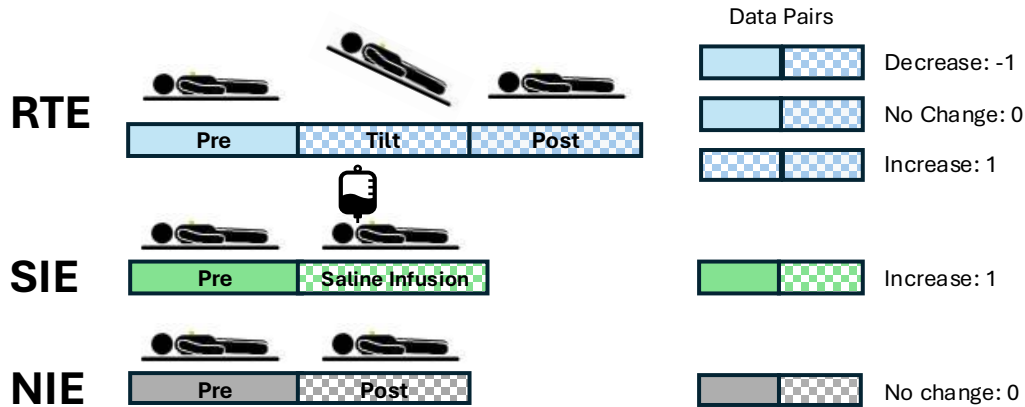
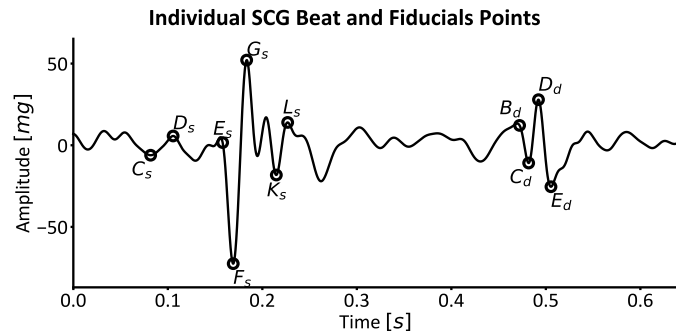


Figure 1: The data, corresponding intervention, and the data pairs with expected outcomes and labels. The data pairs cover how the different recordings are paired to modulate an outcome in preload. One pair results in preload decrease, two pairs result in preload increase, and two pairs result in no change. RTE: Reverse Trendelenburg Experiment, SIE: Salt Infusion Experiment, NIE: No Intervention Experiment.

FP	Definition
Cs	Valley related to atrial systole
Ds	Peak related to atrial systole
Es	Mitral valve closure (MC)
Fs	Post MC valley
Gs	Aortic opening
Ks	Valley related to peak systolic outflow
Ls	Peak Related to peak systolic outflow
Bd	Aortic valve closure (AC)
Cd	Post AC valley
Dd	Post AC peak
Ed	Post Dd valley (pre mitral valve opening)



FP	Time Intervals	Amplitude	Δ Amplitude	Slope
Cs	Cs-Ds, Cs-Es, Cs-Fs, Cs-Gs, Cs-Ks, Cs-Ls, Cs-Bd , Cs Cs-Cd , Cs-Dd , Cs-Ed	Cs	Cs-Ds	Cs-Ds
Ds	Ds-Es , Ds-Fs , Ds-Gs, Ds-Ks, Ds-Ls, Ds-Bd , Ds-Cd , Ds Ds-Dd , Ds-Ed	Ds	Ds-Es	Ds-Es
Es	Es-Fs, Es-Gs, Es-Ks , Es-Ls, Es-Bd , Es-Cd , Es-Dd , Es Es-Ed	Es	Es-Fs	Es-Fs
Fs	Fs-Gs, Fs-Ks , Fs-Ls, Fs-Bd , Fs-Cd , Fs-Dd , Fs-Ed	Fs	Fs-Gs	Fs-Gs
Gs	Gs-Ks , Gs-Ls, Gs-Bd , Gs-Cd , Gs-Dd , Gs-Ed	Gs	Gs-Ks	Gs-Ks
Ks	Ks-Ls, Ks-Bd , Ks-Cd , Ks-Dd , Ks-Ed	Ks	Ks-Ls	Ks-Ls
Ls	Ls-Bd , Ls-Cd , Ls-Dd , Ls-Ed	Ls	Ls-Bd	Ls-Bd
Bd	Bd-Cd, Bd-Dd, Bd-Ed	Bd	Bd-Cd	Bd-Cd
Cd	Cd-Dd, Cd-Ed	Cd	Cd-Dd	Cd-Dd
Dd	Dd-Ed	Dd	Dd-Ed	Dd-Ed
Ed	N/A	Ed	N/A	N/A

Figure 2: The fiducial points identified and the relations with cardiac event and all the features extracted from the initial feature extraction process. The features selected following the initial feature extraction process are marked in bold and underlined.

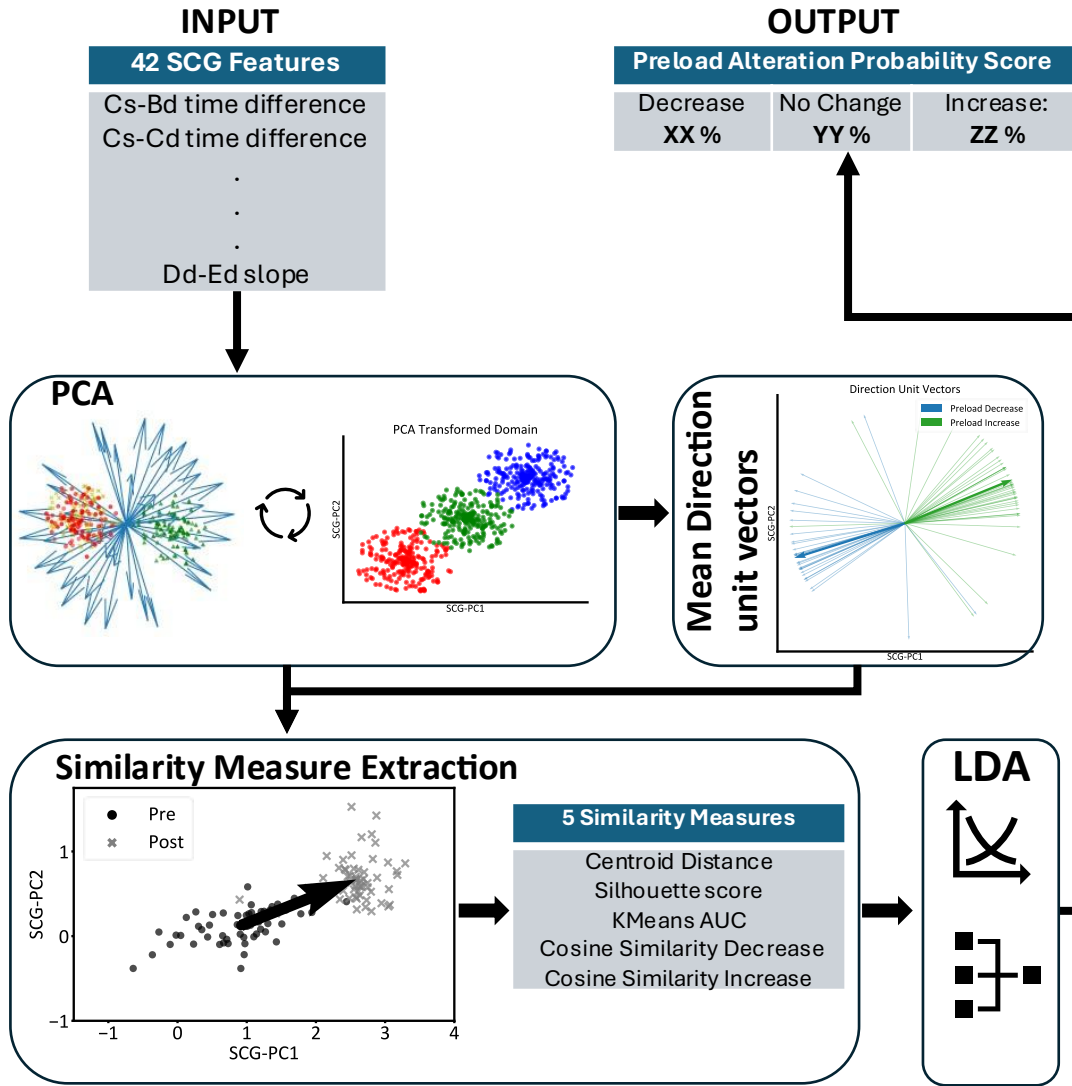


Figure 3: The flow of the algorithm. The 42 SCG features are fitted with a PCA to obtain tw-dimensional SCG-PC feature space. Based on this and labels from train data, mean direction unit vectors for decrease and increase in preload were calculated. In the PCA domain, the similarity measures are calculated and fitted to an LDA resulting in decision boundaries for calculating the preload alteration probability score.

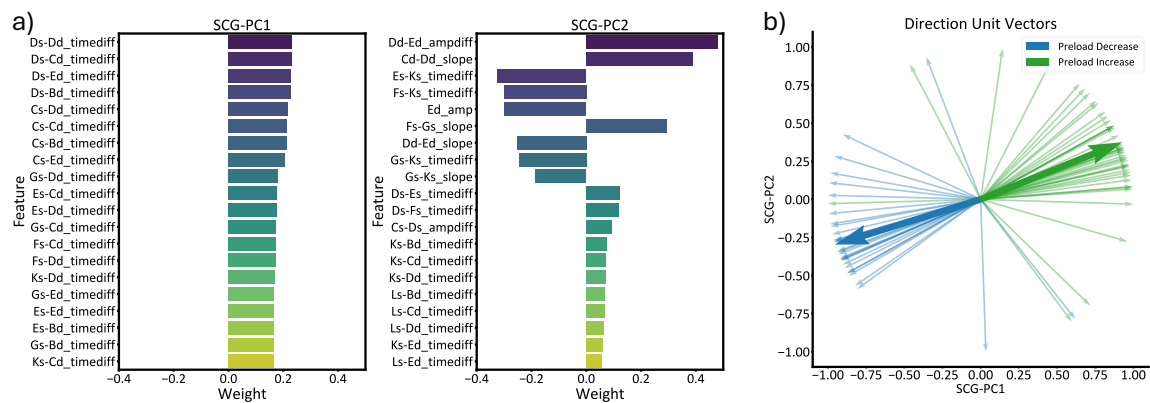


Figure 4: a) The 20 features with highest absolute weights for the two SCG-PCs. b) The unit direction vectors in the two-dimensional SCG-PC space for all training data, where the expected outcome is either preload decrease or preload increase. Additionally, the mean unit direction vector for each expected outcome is highlighted.

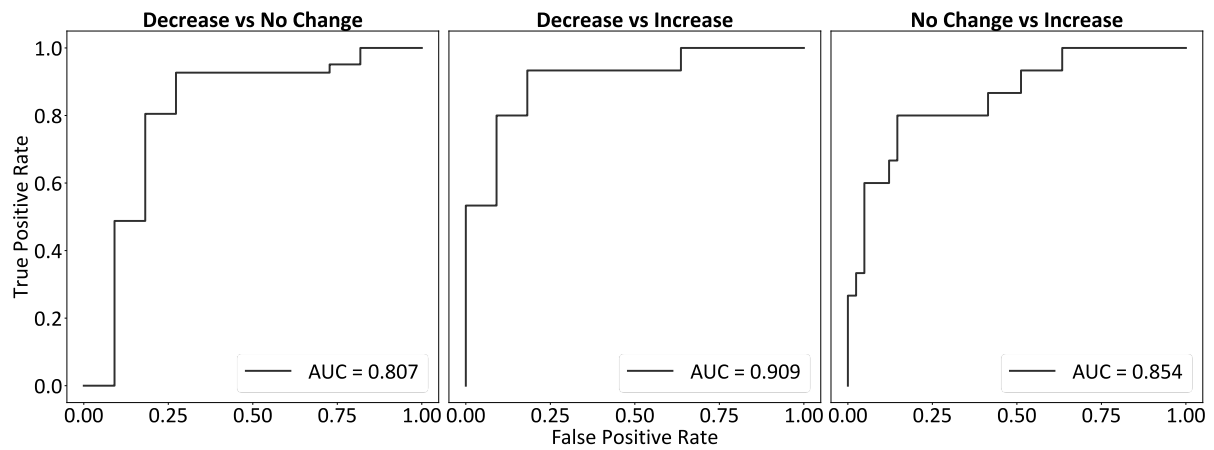


Figure 5: The one vs. one ROC and corresponding AUC. First column is the expected outcome for preload decrease vs no change, second column is preload decrease vs preload increase, and third column is no change vs preload increase.

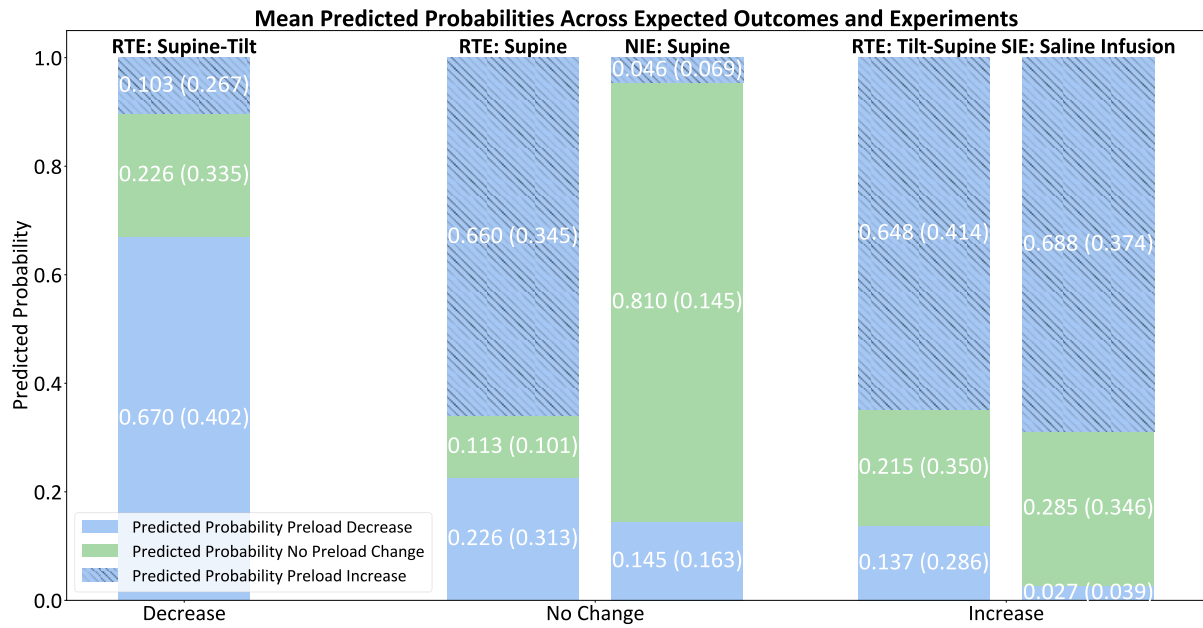


Figure 6: The preload alteration probability score for the three predicted classes for each pair of data. Each bar represents the mean predicted probability for each outcome for a given experiment and pair of data. The x-axis represents the expected outcome, i.e. the pair of data for the given bars. Therefore, the predicted probability of the expected outcome should be high on that same outcome for a good model.

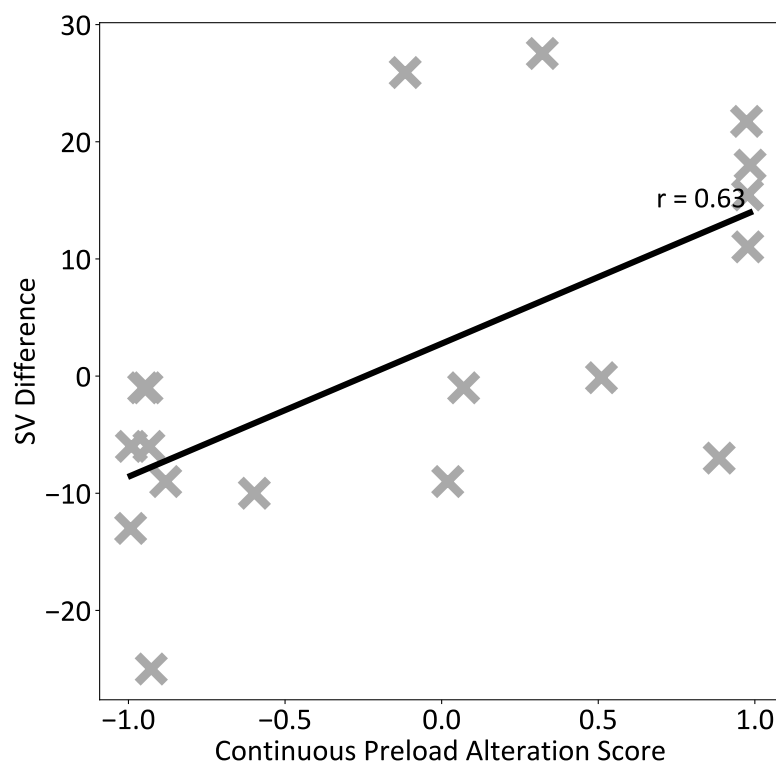


Figure 7: Scatter plot with best fitted line and Pearson correlation for the continuous preload alteration score against the SV change in the corresponding pair of data.

Tables

Table 1: Demographic data and difference in ECG heart rate and TTE measures across the different expected outcomes for train and test data. There is data for each experiment, RTE, NIE, and SIE for each of the expected outcomes: preload decrease, no preload change, and preload increase. Number of subjects, age, and gender is the same for the same experiment across the expected outcomes, since only the type of intervention varies.

Train					
Expected Outcome	Decrease	No Change		Increase	
Experiment	RTE	RTE	NIE	RTE	SIE
N	30	30	83	30	18
Age	46.1 (17.2)	46.1 (17.2)	31.2 (7.0)	46.1 (17.2)	43.7 (15.9)
M/F	12/17	12/17	39/44	12/17	13/5
ECG HR difference	1.6 (6.5)	-2.5 (6.7)	0.8 (2.5)	-2.5 (6.4)	-0.4 (4.0)
TTE HR difference	2.8 (5.6)				1.2 (6.3)
TTE SV difference	-8.1 (5.4)				12.0 (11.9)
TTE CO difference	-0.39 (0.47)				1.0 (0.9)

Test					
Expected Outcome	Decrease	No Change		Increase	
Experiment	RTE	RTE	NIE	RTE	SIE
N	14	14	35	14	8
Age	48.1 (17.1)	48.1 (17.1)	31.4 (7.3)	48.1 (17.1)	49.0 (14.3)
M/F	9/5	9/5	11/24	9/5	7/1
ECG HR difference	-1.7 (7.0)	-3.6 (6.7)	0.70 (3.3)	-1.4 (4.4)	0.0 (4.5)
TTE HR difference	0.0 (5.3)				1.14 (2.85)
TTE SV difference	-8.2 (6.0)				17.1 (8.82)
TTE CO difference	-0.55 (0.72)				0.62 (0.88)

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterialsPreloadAlterationDetection.docx](#)