ChronoECG: Chronological Age Estimation from 12-Lead Electrocardiograms

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ABSTRACT: ChronoECG is a deep learning framework for estimating chronological age from 12-lead ECGs. It was trained on 24,537 curated recordings, with one ECG per patient, using a hybrid architecture that combines convolutional/residual layers, Transformer blocks, a Wavegram branch, and routine clinical metadata. The pipeline included signal-quality auditing, training-only normalization, and patient-independent 70/15/15 splits stratified by age and sex. Across ten internal holdout experiments, ChronoECG achieved an MAE of 7.78 ± 0.12 years and an R^2 of 0.794 ± 0.006 (mean ± SD between runs); age-frequency loss weighting did not improve performance. Younger cohorts were generally overestimated and older cohorts underestimated, consistent with regression toward the mean.

MOTIVATION

Chronological aging produces progressive changes in cardiac structure, conduction and electrophysiology that may be reflected in the 12-lead ECG. Because ECGs are non-invasive, inexpensive and widely available, identifying these age-related patterns could provide a scalable approach for characterizing cardiac aging.

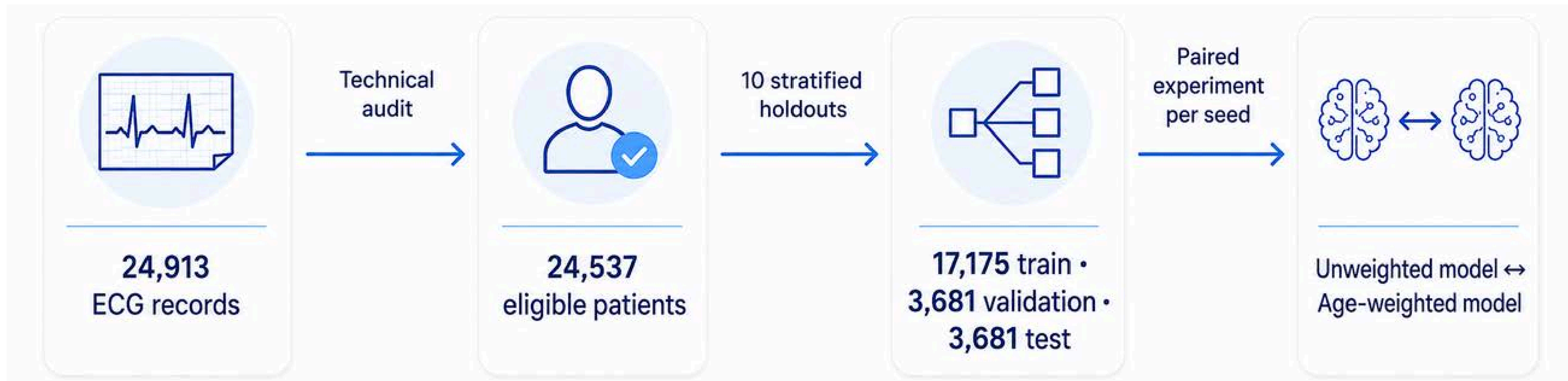
OBJECTIVE

To develop and internally validate ChronoECG, a reproducible deep learning framework for estimating chronological age from 12-lead ECGs, and to determine whether age-frequency loss weighting improves model performance.

METHODOLOGY

ChronoECG was trained on 24,913 recordings, using exactly **one ECG per patient**. After signal-quality auditing, **24,537 recordings were eligible**. Patient-independent **70/15/15 train–validation–test splits** were stratified by age and sex.

The hybrid architecture combines convolutional/residual layers, Transformer blocks, a Wavegram branch and routine ECG metadata. Training used Huber loss, gradient clipping and early stopping. Performance was evaluated across ten holdout seeds, comparing paired unweighted and age-weighted models.

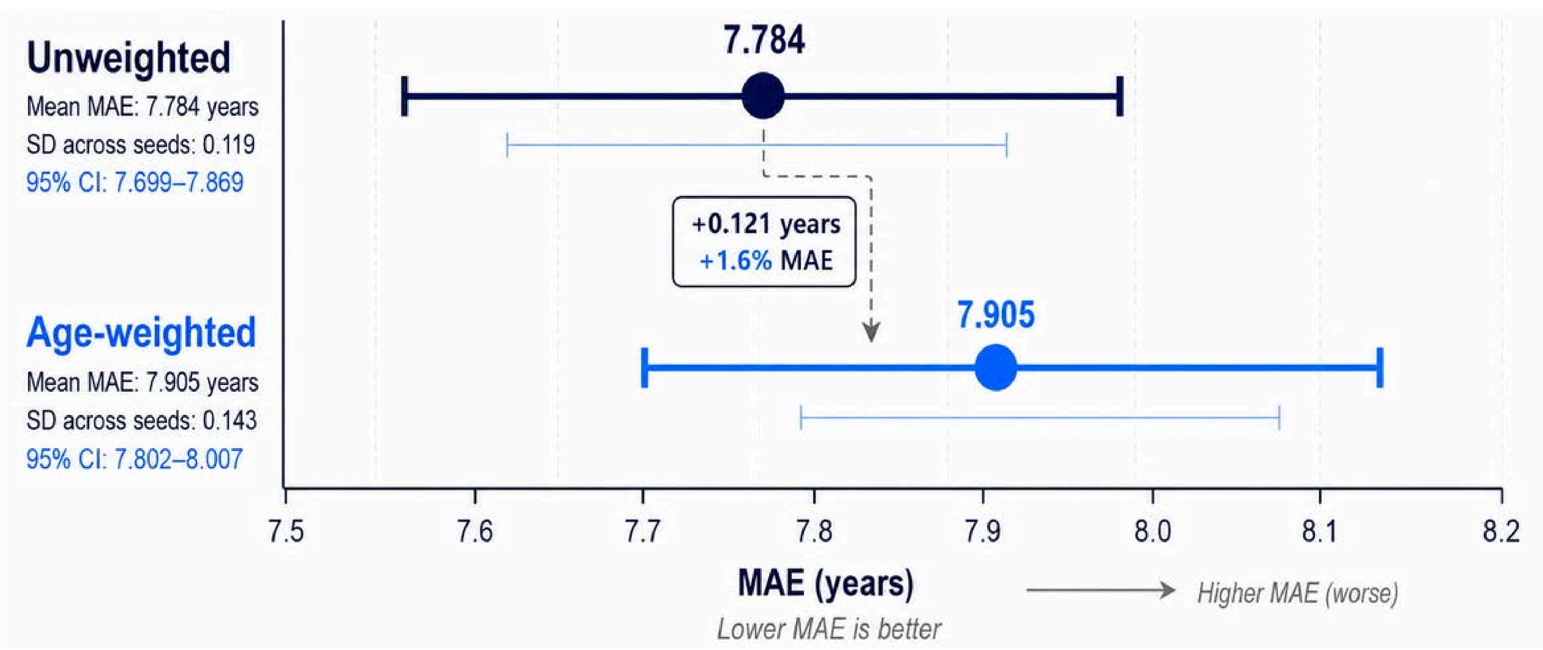


MAIN FINDING

ChronoECG achieved stable performance across ten independent internal holdout experiments, with a mean absolute error of **7.78 ± 0.12 years** and **R^2 = 0.794 ± 0.006**. These results establish a reproducible internal baseline for chronological-age estimation from 12-lead ECGs.

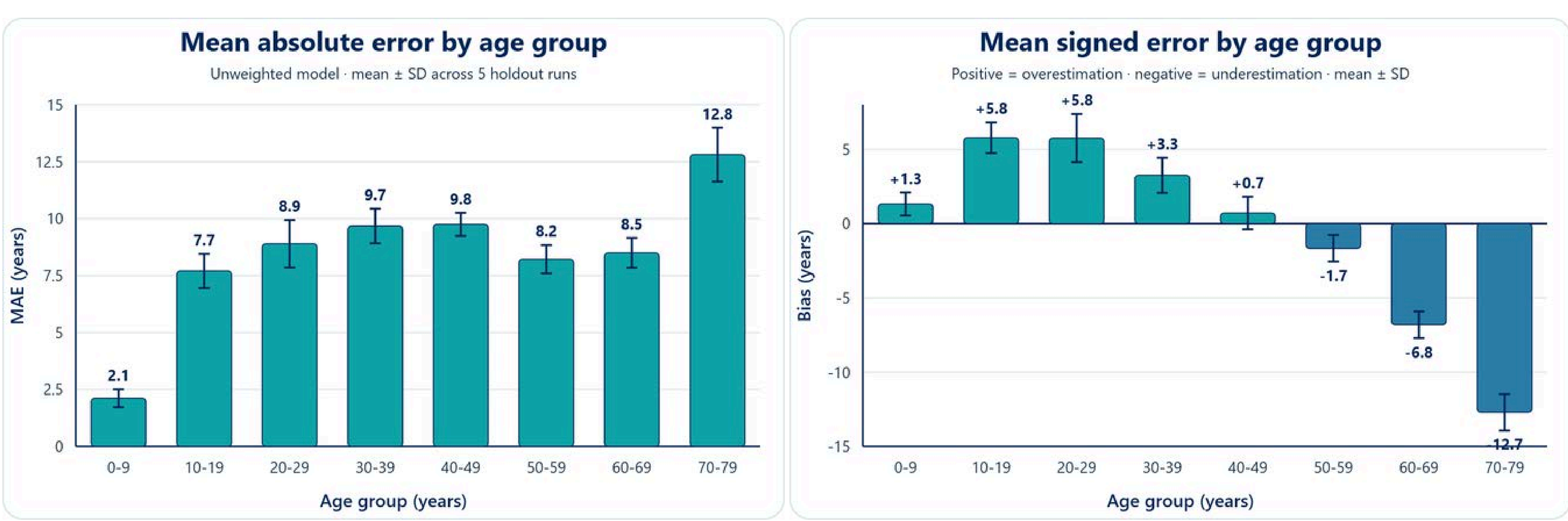
WEIGHTING COMPARISON

Age-frequency loss weighting yielded a higher MAE across ten paired holdout runs, with the weighted model achieving **7.905 ± 0.143 years** compared to **7.784 ± 0.119 years** for the unweighted baseline (mean ± SD across seeds).



AGE-DEPENDENT PERFORMANCE

Performance varied by age group: ChronoECG tended to **overestimate younger patients and underestimate older ones**, with larger errors at the age extremes. Thus, the near-zero global bias masked systematic subgroup errors.

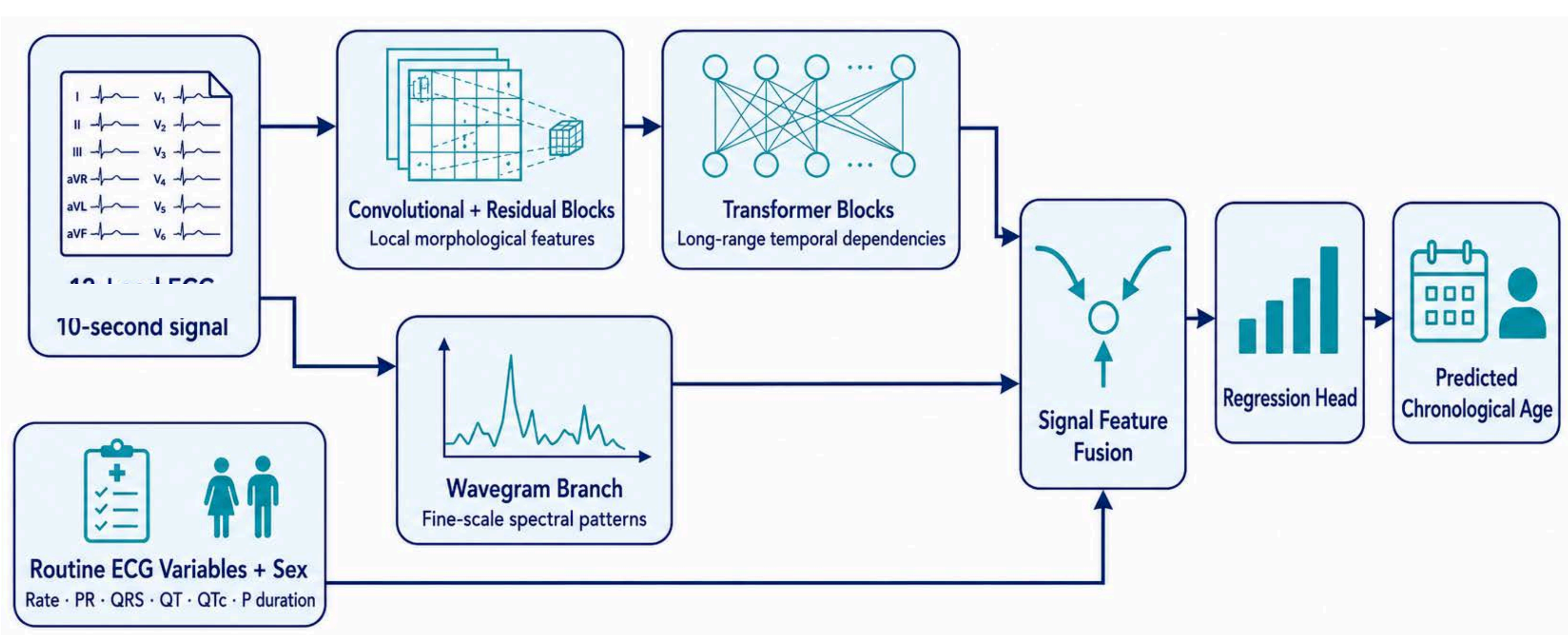


GLOBAL PERFORMANCE

Unweighted training achieved the lowest global error:

ChronoECG ARCHITECTURE

ChronoECG combines convolutional, residual, Transformer and Wavegram branches to extract morphological, temporal and spectral ECG features. These representations are fused with routine ECG variables and sex to estimate chronological age.



COMPARISON WITH PRIOR WORK

WORK	DATASET	MAE
Attia et al., Mayo Clinic	700k ECGs	6.9 years
Ribeiro et al. (Brazil)	1.5M ECGs	8.2 years
Koivisto et al.	750k ECGs	7–9 years
ChronoECG (ours)	**25k ECGs**	**7.78 ± 0.12 years**

Reference values reported in published studies. Datasets and populations differ.

LIMITATIONS

- Internal validation on a single dataset
- Limited representation at age-distribution extremes
- No external population or cross-dataset validation
- No definitive interpretation as biological age or clinical risk

NEXT STEPS

- Validate ChronoECG in larger and more diverse external populations
- Improve calibration across age and sex subgroups
- Investigate whether ECG-predicted age deviations are associated with clinical outcomes