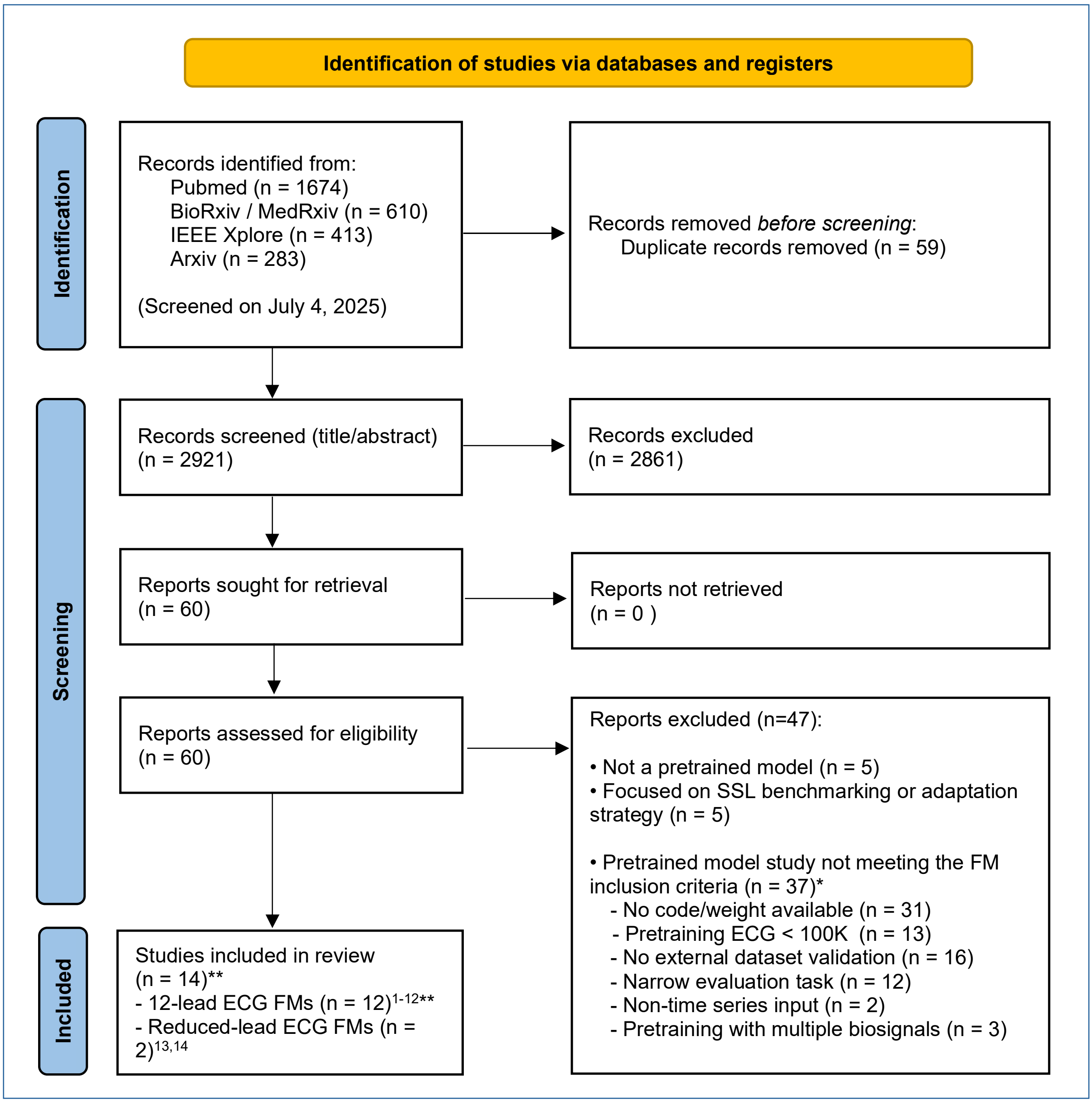
Supplementary Information

Table of Contents

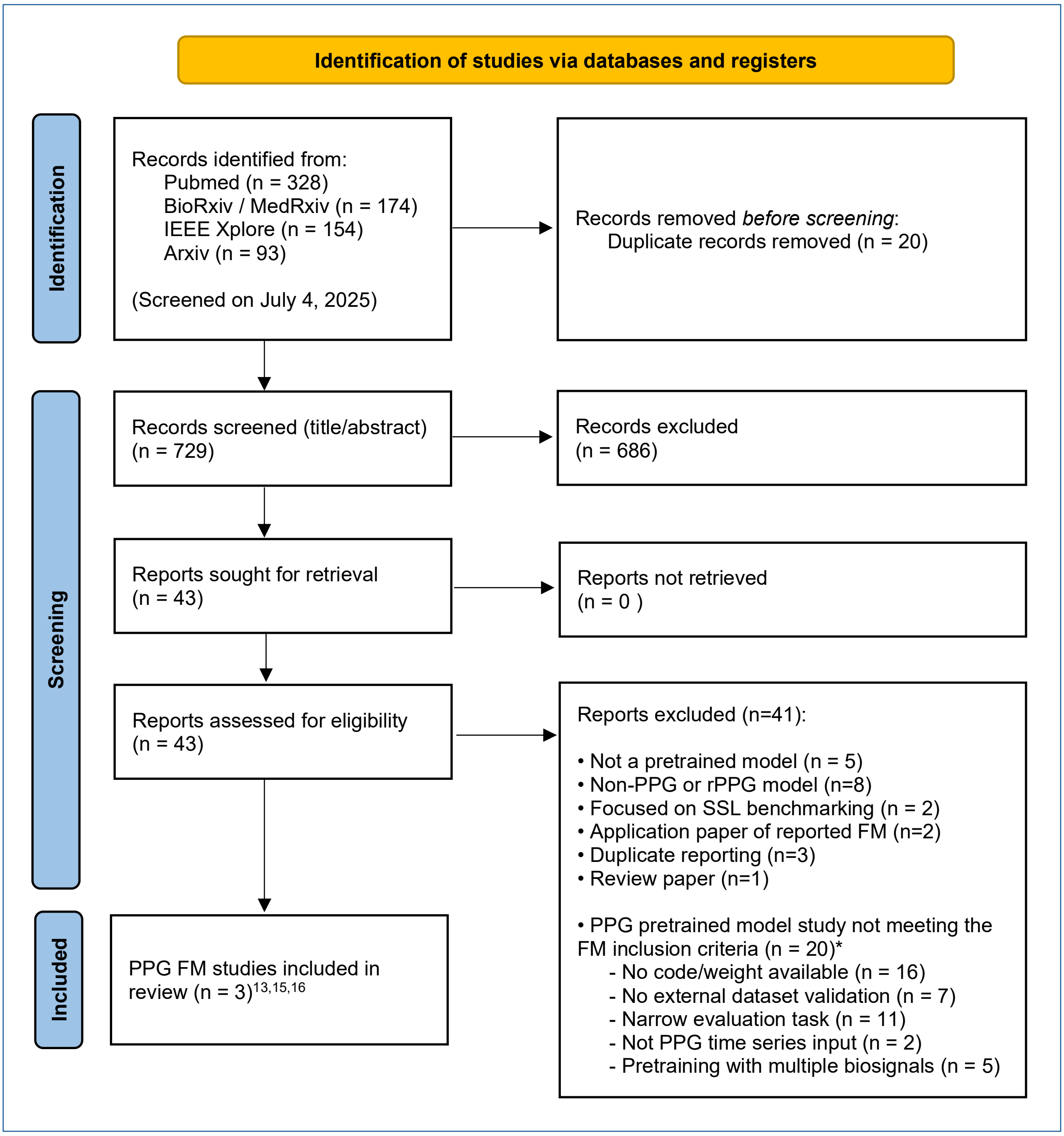
Supplementary Figures

Figure S1. PRISMA flow diagram for selection of ECG foundation models



* Summary of excluded pretrained 12-lead ECG model and pretrained reduced-lead ECG model are detailed in Tables S7 and S8, respectively. Among 37 excluded studies, some had multiple reasons for exclusion.
** 1 paper manually included through reviewing related literature [1]

Figure S2. PRISMA flow diagram for selection of PPG foundation models



* Details of excluded papers are described in Table S9. Among 20 excluded studies, some had multiple reasons for exclusion.

Supplementary Tables

Table S1. Inclusion and exclusion criteria for foundation model selection

Criterion	**Specification**
Inclusion Criteria	
Pretrained model	Study describing a pretrained model with two-stage training and downstream task application
ECG/PPG models with time-series input	Model operates on raw ECG/PPG waveforms (excludes models using ECG images or remote PPG)
Large-scale pretraining dataset	≥100,000 recordings for 12-lead ECG
Multi-task evaluation	Evaluation across multiple downstream task types
External validation	Validation on at least one independent external dataset
Open accessibility of the model	Publicly available code and pretrained weights
Exclusion Criteria	
Methodological focus only	Study focused solely on SSL benchmarking or fine-tuning strategies
Multi-biosignal pretraining	Pretrained jointly on multiple biosignal types (e.g., ECG with EEG, accelerometry, or vital signs)

Table S2. Search strategy for ECG and PPG foundation models

Database	Search Algorithm	Last date of search	Total study retrieved
ECG foundation models			
Pubmed	(("electrocardiogram"[Title/Abstract] OR "ecg"[Title/Abstract] OR "electrocardiography"[Title/Abstract]) AND ("foundation model"[Title/Abstract] OR "self-supervised learning"[Title/Abstract] OR "contrastive learning"[Title/Abstract] OR "pretrained model"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "representation learning"[Title/Abstract] OR "transformer"[Title/Abstract]))	2025-07-04	1674
Arxiv	(all field, separate queries of the following and removed duplicates) “electrocardiogram” AND “foundation model” (22) “electrocardiogram” AND “self-supervised” (52) “electrocardiogram” AND “pretrain” (20) “electrocardiogram” AND “pre-train” (60) “electrocardiogram” AND “contrastive” (54) “electrocardiogram” AND “transformer” (119) “ecg” AND “foundation model” (34) “ecg” AND “self-supervised” (66) “ecg” and “pretrain” (27) “ecg” and “pre-train” (84) “ecg” and “contrastive” (88) “ecg” AND “transformer” (196)	2025-07-04	283
IEEE Xplore	("ECG" OR "electrocardiogram" OR "electrocardiography") AND ("foundation model" OR "self-supervised learning" OR "contrastive learning" OR "pretrained model" OR "transformer")	2025-07-04	413
BioRxiv/ MedRxiv	(ecg OR electrocardiogram OR electrocardiography) AND ("foundation model" OR "self-supervised learning" OR "contrastive learning”)	2025-07-04	610
PPG Foundation Models			
Pubmed	(("photoplethysmography"[Title/Abstract] OR "ppg"[Title/Abstract] OR "photoplethysmogram"[Title/Abstract]) AND ("foundation model"[Title/Abstract] OR "self-supervised learning"[Title/Abstract] OR "contrastive learning"[Title/Abstract] OR "pretrained model"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "representation learning"[Title/Abstract] OR "transformer"[Title/Abstract]))	2025-07-04	328
Arxiv	(all field, separate queries of the following and removed duplicates) “photoplethysmogram” AND “foundation model” (2) “photoplethysmogram” AND “self-supervised” (0) “photoplethysmogram” AND “pretrain” (1) “photoplethysmogram” AND “pre-train” (2) “photoplethysmogram” AND “contrastive” (2) “photoplethysmogram” AND “transformer” (6) “ppg” AND “foundation model” (34) “ppg” AND “self-supervised” (12) “ppg” and “pretrain” (9) “ppg” and “pre-train” (27) “ppg” and “contrastive” (24) “ppg” AND “transformer” (54)	2025-07-04	93

IEEE Xplore	("ppg" OR "photoplethysmogram" OR "photoplethysmography") AND ("foundation model" OR "self-supervised learning" OR "contrastive learning" OR "pretrained model" OR "transformer")	2025-07-04	154
BioRxiv/ MedRxiv	(ppg OR photoplethysmogram OR photoplethysmography) AND ("foundation model" OR "self-supervised learning" OR "contrastive learning")	2025-07-04	174

Table S3. Summary of excluded 12-lead ECG pretrained models and reasons for exclusion

Model (n=25)	Year	Architecture	ECG record number	Reasons for Exclusion				
				No code/ weights	Pretraining ECG size <100k	No external dataset validation	Narrow task	Non-time series input
CAPE[17]	2025	[ResNet-based encoder] + Patient contrastive learning with temporal augmentations	6 M	✓				
ECG-Nest-FM[18]	2025	[Frequency-focused transformer with nested embeddings and Matryoshka-style decoder] + masked reconstruction + VICReg	910 K	✓				
ECGFM[19]	2025	[CNN-based encoder + Transformer decoder + LSTM caption head] + CPC + binary classification + diagnostic text generation (multi-task pretraining)	1 M	✓				
Hu et al.[20]	2025	[Custom ResNet (15-block CNN)] + supervised multi-label classification (weighted BCE for imbalance)	1.6 M	✓		✓		
Kumar B et al.[21]	2025	[CNN encoder + projection head] + contrastive learning (InfoNCE; MoCo negatives; augmentations: time-warp, inversion, noise, lead permutation)	n/a	✓	✓	✓	✓	
LCD[22]	2025	[ViT encoder + small Transformer decoder] + masked reconstruction + lead-specific correlation/decorrelation contrastive learning (intra-lead + inter-lead invariance; redundancy reduction)	35 K		✓			
LFBT[23]	2025	[Multi-branch CNN encoders + Multi-Branch Concatenation (MBC)] + Barlow Twins with fused intra-/inter-lead contrastive loss (lead-aware redundancy reduction; no negatives)	79 K		✓		✓	
Liu et al.[24]	2025	[BYOL framework (CNN/BiLSTM encoder + projection head)] + self-supervised contrastive learning (negative-free; longitudinal augmentations with BiLSTM-CNN + TimeGAN)	4.9 M	✓				
SuPreME[25]	2025	[ViT encoder (ECG patch encoder) + Cardiac Fusion Network (Transformer decoder)] + supervised multimodal learning (LLM-extracted cardiac queries + ECG feature fusion; multi-label classification)	770 K	✓				
TSSL[26]	2025	[1D-ResNet18 encoder] + temporal order prediction (TSL, segment shuffling) + cross-lead contrastive learning (SCL, InfoNCE; positives = same-individual views across time; no required augmentations)	39 K	✓	✓	✓	✓	
AnyECG[27]	2024	[Transformer backbone with Cross-Mask Attention + vector-quantized rhythm codebook tokenizer] + multi-view synergistic decoding (morphology reconstruction, frequency reconstruction with wavelets, demography prediction)	53 K	✓		✓		

Model (n=25)	Year	Architecture	ECG record number	Reasons for Exclusion				
				No code/ weights	Pretraining ECG size <100k	No external dataset validation	Narrow task	Non-time series input
ETP[28]	2024	[Dual encoders: ECG encoder + frozen language model (text encoder, CLIP-style)] + ECG–text contrastive learning (cross-modal alignment; negatives = mismatched ECG–text pairs) + self-supervised ECG contrastive learning (InfoNCE with augmentations: segmentation, inversion)	29 K	✓	✓	✓		
LC-CL[29]	2024	[Main single-lead encoder (lead I) + multiple helper encoders for other lead combinations] + multi-view contrastive learning (NT-Xent; positives = same-lead/combination pairs; losses: main, helper, entity; augmentations: jitter)	1.4 M	✓			✓	
MAE-MoCo / MAE-Nextclip[30]	2024	[ViT encoder + dual pathways (masked input for MAE, augmented input for MoCo) + momentum encoder] + combined objectives: masked reconstruction (MAE, MSE on masked patches) + contrastive instance discrimination (MoCo, InfoNCE; positives = same ECG, negatives = queue-based different ECGs)	40 K	✓	✓	✓	✓	
Moody et al.[31]	2024	[ViT encoder (waveform patching, 12-block Transformer) + small Transformer decoder] + masked signal modeling (reconstruct masked ECG patches with L2 loss, 60% masking ratio)	800 K	✓				
Sawano et al.[32]	2024	[ViT encoder (Base/Large/Huge) + MAE decoder] + masked autoencoding (random masking at 75% ratio, reconstruct missing ECG patches with MSE loss; explored alternative ratios 50%/90% and masking strategies: random, grid, per-lead)	130 K	✓				
Song et al.[33]	2024	ViT + 1D convolutional patch embedding with dual forward paths: masked generative learning via MAE-style reconstruction and contrastive learning via InfoNCE on augmented ECGs, trained jointly using a hybrid loss	1.3 M	✓			✓	
HeartBEiT[34]	2023	[ViT (12-layer, 86M params) + BEiT-style discrete image tokenizer + Transformer decoder] + masked image modeling (40% patch masking, predict discrete tokens using DALL-E pretrained tokenizer)	8.5 M	✓				✓
Zhang et al.[35]	2023	[1D/2D ViT encoder + lightweight Transformer decoder] + masked autoencoding with three strategies: temporal masking (MTAE), lead masking (MLAE), and combined masking (MLTAE)	12 K	✓	✓	✓	✓	

Model (n=25)	Year	Architecture	ECG record number	Reasons for Exclusion				
				No code/ weights	Pretraining ECG size <100k	No external dataset validation	Narrow task	Non-time series input
Bo et al.[36]	2022	[ResNet-18 encoder + 1D U-Net adversarial mask generator] + contrastive learning (SimCLR objective; adversarially generated masks target diagnostically relevant regions)	88 K	✓	✓	✓		
CRT[37]	2022	[CNN local feature extractors + Transformer encoder/decoder] + cross-domain reconstruction (time–frequency with magnitude & phase; dropping instead of masking; progressive curriculum + instance discrimination)	22 K	✓	✓	✓	✓	
CT-HB[38]	2022	[CausalCNN backbone] + contrastive learning with heartbeat sampling (anchor–positive from same ECG, negatives from other ECGs; multi-similarity loss) → ensemble heartbeat representations for patient-level ECG classification	705 K	✓	✓			
Li et al.[39]	2022	[BiLSTM-CNN + TimeGAN (for augmentation) + CNN/Transformer classifier] + contrastive learning (two augmented views per ECG, projection head, maximize similarity; negatives = other ECGs)	n/a	✓	✓	✓		
Oh et al.[40]	2022	[Wav2Vec 2.0 (CNN feature encoder + Transformer context encoder, quantization module)] + combined contrastive learning (local via Wav2Vec 2.0 masked time-step prediction, global via CMSC temporal segment invariance) + Random Lead Masking (ECG-specific augmentation for lead-agnostic training)	19 K		✓	✓		
Mehari et al.[41]	2021	[ResNet-style CNN backbone] + systematic evaluation of SSL objectives (CPC, SimCLR, BYOL, SwAV) with ECG augmentations → identified best augmentation pair (time-out + random resized crop), SimCLR best in linear probe, BYOL best after fine-tuning	54 K		✓	✓	✓	

BCE, binary cross-entropy; BEiT, Bidirectional Encoder representation from Image Transformers; BiLSTM, bidirectional long short-term memory; BYOL, Bootstrap Your Own Latent; CLIP, contrastive language–image pretraining; CNN, convolutional neural network; CPC, contrastive predictive coding; CMSC, cross-modal supervised contrast; CRT, cross-domain reconstruction transformer; ECG, electrocardiogram; EMA, exponential moving average; InfoNCE, noise-contrastive estimation loss with in-batch negatives; K, thousand; LSTM, long short-term memory; M, million; MAE, masked autoencoder; MoCo, momentum contrast; MSE, mean squared error; n/a, not available; NT-Xent, normalized temperature-scaled cross-entropy loss; RLM, random lead masking; SimCLR, simple contrastive learning of representations; SSL, self-supervised learning; SCL, self-supervised cross-lead contrast; SwAV, Swapping Assignments between multiple Views; TSL, temporal shuffling loss; U-Net, encoder–decoder convolutional network with skip connections; VICReg, variance–invariance–covariance regularization; ViT, vision transformer

1. Code and pretrained weights (when available) can be found at:
LCD (code/weights) - https://github.com/Aiwiscal/ECG_SSL_LCD
LFBT (code/weights) - https://github.com/Aiwiscal/ECG_SSL_LFBT
TSSL (code) - https://github.com/cwp9731/temporal-spatial-self-supervised-learning
HeartBEiT (code) - https://github.com/akhilvaid/HeartBEiT
Bo et al., 2022 (code) - https://github.com/jessica-bo/advmask_ecg
Oh et al., 2022 (code/ weights) - https://github.com/Jwoo5/fairseq-signals
Mehari et al. 2021 (code/ weights) - https://github.com/tmehari/ecg-selfsupervised

Table S4. Summary of excluded single-lead ECG pretrained models and reasons for exclusion

Model	Year	Input data	Architecture	Pretrain Dataset size	Reasons for Exclusion				
					No code/ weights	No Ext. dataset	Narrow task	Non-time series input	Pretrain on multiple signal
ECG-SRL[42]	2025	ECG	[xResNet50] + BYOL-style contrastive learning	67 K (SL)/ 260 K (SSL) 10-sec segments	✓		✓		
CSFM[43]	2025	ECG, PPG	*Insufficient description*	2.6 M/ 0.27 M (ECG/PPG) Segments	✓				✓
MIRA[44]	2025	ECG, PPG, EEG, respiration	[Transformer backbone with Continuous-Time Rotary Positional Encoding (CT-RoPE) + Frequency-specific Mixture-of-Experts] + [Neural ODE dynamics block] + Pretraining (Masked modeling + Forecasting across multi-modal signals)	454 B time points	✓				✓
Tudjarski et al.[45]	2025	ECG	[Transformer (RoBERTa) ECG-token encoder] + masked language modeling (self-supervised)	98 hr, 22.8 M heartbeat	✓			✓ (ECG derived feature)	
Wearable-Echo-FM[46]	2025	ECG	[7-layer 1D CNN ECG encoder + RoBERTa Transformer text encoder] + CLIP-style Multi-Modal Contrastive Learning: ECG↔Echo Report Text	274 K ECG-echo pair	✓	✓			
Abbaspourazad et al.[47]	2024	ECG, PPG (wearable)	[EfficientNet-style 1D CNN] + Contrastive SSL (InfoNCE + KoLeo regularization)	3.7 M/ 20 M (ECG/PPG) 10-sec segments	✓	✓			
Kite et al.[48]	2024	ECG (4 lead, telemetry)	[Multi-Lead ResNet Encoder] + Patient Contrastive Learning of Representations (PCLR) with MoCo	8.9 M 60-sec segments	✓ (not sufficient)	✓			
NormWear[49]	2024	PPG, ECG, EEG, GSR, IMU	[ViT with Continuous wavelet transform (CWT) tokenization + Channel-aware attention] + Hybrid SSL (Reconstructive MAE + Sensor-Semantic Alignment)	106 K samples (augmentation by factor of 10)					✓
Wang et al.[50]	2024	ECG	[1D ViT] + MAE	1.14 M input segments	✓				
ECG-SL[51]	2023	ECG	[Two-Stage Hybrid Architecture: 1D CNN Auto-Encoder + Transformer] + Hierarchical SSL: Structural Reconstruction → BERT-style Masked Segment Modeling	25 M heartbeat segments	✓				

Model	Year	Input data	Architecture	Pretrain Dataset size	Reasons for Exclusion				
					No code/ weights	No Ext. dataset	Narrow task	Non-time series input	Pretrain on multiple signal
REBAR[52]	2023	(HAR) ACC/GYR, PPG, ECG	[1D ResNet18 Encoder + Retriever Module] + Contrastive Learning + Reconstruction Decoder (Hybrid: Combines contrastive learning (InfoNCE) with reconstruction loss)	PPG: 1.3 K 1-min subsequences	✓	✓	✓		
SiamAF[53]	2023	PPG+ ECG	[1D ResNet-34] + Siamese Cross-Modal Learning (Agreement Loss + Supervised Classification)	5.8 M ECG/PPG 30-sec segments			✓		

ACC, accelerometer; BERT, Bidirectional Encoder Representations from Transformers; BYOL, Bootstrap Your Own Latent; CLIP, Contrastive Language–Image Pretraining; CNN, convolutional neural network; ECG, electrocardiogram; EEG, electroencephalogram; GSR, galvanic skin response; GYR, gyroscope; HAR, human activity recognition; hr, hour; IMU, inertial measurement unit; InfoNCE, Information Noise-Contrastive Estimation; K, thousand; KoLeo, Kozachenko–Leonenko regularization; M, million; MAE, masked autoencoder; min, minute; MoCo, Momentum Contrast; Neural ODE, neural ordinary differential equation; PPG, photoplethysmography; ResNet, Residual Network; sec, seconds; SSL, self-supervised learning; ViT, Vision Transformer.

1. Some models are listed in both Table S5 (ECG-based models) and Table S6 (PPG-based models) because they used both ECG and PPG as input during pretraining.

2. Code and pretrained weights (when available) can be found at:
NormWear (code/weights) - https://github.com/Mobile-Sensing-and-UbiComp-Laboratory/NormWear
REBAR (code) - https://github.com/maxxu05/rebar
SiamAF (code/weights) - https://github.com/chengstark/SiamAF

Table S5. Summary of excluded PPG pretrained models and reasons for exclusion

Model	Year	Input data	Architecture	Pretrain dataset size	Reasons for Exclusion				
					No code/ weights	**No Ext. dataset**	**Narrow task**	**Non-time series input**	**Pretrain on multiple signal**
CSFM[43]	2025	ECG, PPG	*Insufficient description*	2.6 M/ 0.27 M (ECG/PPG) segments	✓				✓
CSleep[54]	2024	PPG	[Shared CNN Encoder + Dual LSTM + Cross-Task Attention + Cross-Granular Heads] + SimCLR-style Contrastive Pretraining	2 K subjects	✓		✓		
GPT-PPG[55]	2025	PPG	[GPT-style Decoder-only Transformer] + Tokenized PPG + Pretraining via Next-Token Prediction (Autoregressive MLM)	200 M 30-sec segments	✓				
Kazemi et al.[56]	2025	PPG	[Multi-Scale Residual CNN with dilated residual inception blocks] + supervised regression on RR (Smooth L1/Huber loss) with transfer learning	2 M 32 sec segments			✓		
LSM-2[57]	2025	PPG + ACC + Temp.+ skin conductance + altimeter	[ViT-1D Encoder-Decoder + Adaptive Inherited Masking (AIM)] + MAE-style Reconstruction Pretraining	40 M hours	✓			✓ PPG derived features	✓
MIRA[44]	2025	ECG, PPG, EEG, respiratory	[Transformer backbone with CT-RoPE] + [Frequency-specific Mixture-of-Experts] + [Neural ODE dynamics block] + Pretraining (Masked modeling + Forecasting across multi-modal signals)	454 B time points	✓				✓
PhysCL[58]	2025	PPG	[ConvNeXt CNN encoder] + knowledge-aware contrastive SSL (NT-Xent) pretraining with fiducial-aware augmentations & feature reconstruction; followed by supervised fine-tuning for BP regression	~450~700 hrs (~0.5~0.8M 5-sec segment)	✓	✓	✓		
Wu et al. [59]	2025	PPG	[1D CNN + BiLSTM] + SimCLR Contrastive Pretraining	~1.2 M 20-sec segments	✓		✓		
Abbaspourazad et al. [47]	2024	ECG, PPG (wearable)	[EfficientNet-style 1D CNN] + Contrastive SSL (InfoNCE + KoLeo regularization)	3.7 M/ 20 M (ECG/PPG) 10-sec segments	✓	✓			
EnhancePPG[60]	2024	PPG	[1D CNN + MHCA] + U-Net-style Autoencoder (Reconstructive Pretraining)	493 K 8-sec segments	✓		✓		

Model	Year	Input data	Architecture	Pretrain dataset size	Reasons for Exclusion				
					No code/ weights	No Ext. dataset	Narrow task	Non-time series input	Pretrain on multiple signal
Le et al.[61]	2024	PPG	[PPG Signal Transformer Encoder with Preprocessing Pipeline] + 3 SSL comparison (Masking, Contrastive, DINO) + Novel Smooth InfoNCE Loss + Fine-tuning on limited labeled data	80 K pulse segments	✓	✓	✓		
LSM[62]	2024	PPG + ACC + Temp.+ skin conductance + altimeter	[ViT-based masked autoencoder (LSM-Base, 110M)] + masked signal reconstruction SSL (MAE with 80% random masking)	40 M hr	✓			✓ PPG derived features	✓
NormWear[49]	2024	PPG, ECG, EEG, GSR, IMU	[ViT with CWT tokenization + Channel-aware attention] + Hybrid SSL (Reconstructive MAE + Sensor-Semantic Alignment)	106 K samples (augmentation by factor of 10)					✓
REGLE[63]	2024	PPG, spirogram	[VAE] + Unsupervised reconstruction for genetic discovery	85 K segments		✓	✓		
SiamQuality[64]	2024	PPG	[ResNet Encoder + Projector + Predictor (SimSiam framework)] + Quality-aware contrastive SSL (pairs high- vs. low-quality PPG segments; curriculum learning by increasing artifact severity)	36M 30sec segments	✓				
TS2TC[65]	2024	PPG	[PPG Signal Multi-Domain Encoder (Temporal + Spectrogram + Mixed)] + Generative Self-Supervised Pretraining + Dual-Process Transfer Learning	250 K	✓				
Mwaniki et al.[66]	2023	PPG	[1D ResNet-50 encoder (2-channel input)] + contrastive SSL (patient-level positives/negatives, NCE loss)	~470 hrs across ~7,500 pediatrics	✓	✓	✓		
REBAR[52]	2023	(HAR) ACC/GYR, PPG, ECG	[1D ResNet18 Encoder + Retriever Module] + Contrastive Learning + Reconstruction Decoder (Hybrid: Combines contrastive learning (InfoNCE) with reconstruction loss)	PPG: 1.3 K 1-min subsequence	✓	✓	✓		
SiamAF[53]	2023	PPG+ ECG	[1D ResNet-34] + Siamese Cross-Modal Learning (Agreement Loss + Supervised Classification)	5.8 M ECG/PPG 30-sec segments			✓		
Ghorbani et al.[67]	2022	PPG	[CNN Autoencoder] + self-supervised reconstruction (mean squared error)	14 subject, ~2.5 hr/ subject	✓	✓	✓		

ACC, accelerometer; BiLSTM, bidirectional long short-term memory; BP, blood pressure; CNN, convolutional neural network; ConvNeXt, convolutional next-generation CNN backbone; CT-RoPE, continuous-time rotary positional embedding; CWT, continuous wavelet transform; ECG, electrocardiogram; EEG, electroencephalogram; GSR, galvanic skin response; GYR, gyroscope; hr, hour; IMU, inertial measurement unit; K, thousand; KoLeo, Kozachenko–Leonenko regularization; LSTM, long short-term memory; MAE, masked autoencoder; MHCA, multi-head convolutional attention; min, minute; MLM, masked language modeling; M, million; NCE/InfoNCE, noise-contrastive estimation; NT-Xent, normalized temperature-scaled cross entropy; ODE, ordinary differential equation; PPG, photoplethysmography; ResNet, residual neural network; RoPE, rotary positional embedding; RR, respiratory rate; sec, second; SimCLR, simple framework for contrastive learning of representations; SSL, self-supervised learning; ViT, vision transformer; VAE, variational autoencoder

1. Some models are listed in both Table S5 (ECG-based models) and Table S6 (PPG-based models) because they used both ECG and PPG as input during pretraining.

2. Code and pretrained weights (when available) can be found at:
Kazemi et al. (code/weights) - https://github.com/kazemikianoosh/RR_Estimation
NormWear (code/weights) - https://github.com/Mobile-Sensing-and-UbiComp-Laboratory/NormWear
REGLE (code/weights) – https://github.com/Google-Health/genomics-research/tree/main/regle
SiamQuality (code) - https://github.com/chengding0713/SiamQuality
Mwaniki et al (code) - https://github.com/pmwaniki/ppg-analysis
REBAR (code) - https://github.com/maxxu05/rebar
SiamAF (code/weights) - https://github.com/chengstark/SiamAF

Table S6. Architectural, reporting details of included 12-lead ECG foundation models

Model	ECG Lead/ sample rate	Architectural characteristic	Performance			Data efficiency	Reduced lead analysis	Fairness	Privacy	Compute efficiency	Interpretability (representation-level)	Explainability (prediction-level)
			LP	FT	Zero -shot							
ECG-FM[2] (2024)	12 / 500Hz	[CNN + Transformer (WCR)] + masked lead modeling + dual contrastive learning (SimCLR-style local + CMSC-style global) + random lead masking	✓	✓	-	✓	✗	✗	✗	Hardware, training time	UMAP representation clustering	Attention based saliency map
DeepECG -SSL[3] (2025)	12 / n/a	[CNN + Transformer (WCR)] + masked lead modeling + dual contrastive learning (SimCLR-style local + CMSC-style global) + random lead masking	✗	✓	-	✓	✗	✓	✓	Hardware, CO2 emission, training time	✗	LIME, Grad-CAM
HuBERT-ECG[4] (2024)	12 / 100Hz	[Wav2Vec 2.0-style CNN + Transformer] + masked prediction of quantized latent ECG embeddings using cluster-based pseudo-labels (multi-task ensemble of clustering models, refined iteratively)	✗	✓	-	✓	✗	✗	✗	Hardware, training time proxy: No. of steps per dataset	✗	Attention map
CPC[1] **(2025)**	12/ 240Hz	[4-layer CNN encoder + 4-layer S4 (Structured State Space Model)] + Contrastive Predictive Coding (CPC) predicting future latent representations	✓	✓	-	✓	✗	✗	✗	Hardware, training time	CKA layer similarity heatmap	✗
ST-MEM[5] **(2024)**	12 / 250Hz	[ViT-B, lead-wise decoder] + masked reconstruction (spatio-temporal patchifying)	✓	✓	-	✓	✓	✗	✗	Hardware	t-SNE + GMM representation clustering	✗
ECG-JEPA[6] (2024)	12 (8) / 250Hz	[Transformer (student–teacher, EMA teacher, CroPA attention)] + masked representation prediction in latent space (time-synchronized patch masking across leads)	✓	✓	-	✓	✓	✗	✗	Training time, hardware	UMAP representation clustering, CroPA attention visualization	✗
HeartLang[7] (2025)	12 / 100Hz	[ST-ECGFormer Transformer] + heartbeat tokenization (QRS-based) + discrete ECG vocabulary (EMA-vector quantization) + masked token prediction (MLM)	✓	✓	-	✓	✓	✗	✗	Hardware	Textual; ECG vocab visualization	✗

Model	ECG Lead/ sample rate	Architectural characteristic	Performance			Data efficiency	Reduced lead analysis	Fairness	Privacy	Compute efficiency	Interpretability (representation-level)	Explainability (prediction-level)
			LP	FT	Zero -shot							
ESI[8] (2024)	12 / 500Hz	[1D ConvNext v2 + Clinical Text Encoder (BioLinkBERT)] + RAG based LLM-generated expert prompts + dual contrastive loss	✓	✓	✓	✓	✗	✗	✗	Hardware	✗	✗
MERL[9] (2024)	12 / 500Hz	[1D-ResNet18+ Clinical Text Encoder (Med-CPT)] + Multi-modal contrastive pretraining + clinical knowledge enhanced prompting at test time	✓	✗	✓	✓	✗	✗	✗	Hardware	✗	✗
MELP[10] (2025)	12 / 500Hz	[Wav2Vec 2.0 + Transformer Encoder (Med-CPT) + GPT-style Text Decoder] + Multi-scale cross-modal supervision (Token + Beat + Rhythm levels) + Cardiology-specific language model pretraining	✓	✓	✓	✓	✗	✗	✗	Hardware	t-SNE representation clustering	✗
KED[11] (2024)	12 / 100Hz	[1D CNN signal encoder + Transformer label query network + BioClinicalBERT] + signal–text–label contrastive learning (AugCL, CLIP/UniCL-inspired) → knowledge-augmented, query-based multi-label ECG diagnosis	✗	✓	✓	✓	✗	✗	✗	Hardware	t-SNE of text-label/query embedding space	Grad-CAM
ECGFounder[12] (2024)	12 / 500Hz	[1D RegNet-based CNN (Net1D) + Bottleneck blocks + Channel-wise attention + Skip Connections] + Supervised pretraining on 10M ECGs (150 labels)	✓	✓	-	✗	✓	✗	✗	✗	✗	✗

Abbreviations: AugCL, augmented contrastive learning; CKA, centered kernel alignment; CLIP, contrastive language–image pretraining; CMSC, cross-modal supervised contrast; CNN, convolutional neural network; CO_2, carbon dioxide; CroPA, cross-pattern attention; ECG, electrocardiogram; EMA, exponential moving average; FT, fine-tuning; GMM, Gaussian mixture model; Grad-CAM, gradient-weighted class activation mapping; IPA, inflection point area ratio; LIME, local interpretable model-agnostic explanations; LP, linear probing; Med-CPT, medical clinical prompt tuning; MLM, masked language modeling; MoE, mixture of experts; n/a, not available; Net1D, one-dimensional RegNet-based convolutional neural network; No., number; PPG, photoplethysmography; RAG, retrieval-augmented generation; RLM, random lead masking; SimCLR, simple contrastive learning of representations; SimSiam, simple siamese contrastive framework; SQI, signal quality index; ST-ECGFormer, spatiotemporal ECG transformer; sVRI, stress-induced vascular response index; t-SNE, t-distributed stochastic neighbor embedding; UMAP, uniform manifold approximation and projection; UniCL, unified contrastive learning; WCR, wav2vec 2.0 + CMSC + RLM hybrid objective.

Table S7. Architectural, reporting details of included single-lead ECG/ PPG foundation models

Model	ECG Lead/ sample rate	Architectural characteristic	Performance			Data efficiency	Reduced lead analysis	Fairness	Privacy	Compute efficiency	Interpretability (representation-level)	Explainability (prediction-level)
			LP	FT	Zero-shot							
Single Lead ECG / PPG Foundation Models												
ECG-PT, PPG-PT[13]	ECG- lead 1/ 100 Hz, resample PPG: - / 50Hz, resample	[Decoder-only Transformer (GPT-style)] + Next-token prediction (cross-entropy loss) on tokenized ECG/PPG (integer-scaled windows: 5s 100 Hz, ECG; 10s 50 Hz PPG)	✗	✓ (partial FT)	-	✗	-	✗	✗	Hardware, training time, finetuning time	Attention-head analysis, embedding phase clustering	Attention map
HeartBERT[14]	1 lead - ML II (lead unspecified for PTB-XL) / 360Hz, resample	[RoBERTa-based Transformer Encoder] + Lloyd–Max quantization (100-level, 360 Hz resampled ECG → ASCII "synthetic language") + SentencePiece BPE tokenizer → MLM on discretized ECG text	✓	✓	-	✗	-	✗	✗	Hardware	✗	✗
PaPaGei-S, PaPaGei-P[15]	- / 125Hz, resample	[ResNet-style 1D CNN (18 conv blocks, 32→256 filters) + FC projection head (512-d) (+ 2 MoE regression heads for PaPaGei-S)] + Subject-aware contrastive SSL (PaPaGei-P) / Morphology-aware SSL: sVRI-based contrastive & IPA/SQI regression (PaPaGei-S)	✓	-	-	✓	-	yes, but limited (skin tone analysis)	✗	Hardware	Morphology objective ablation; inter-participant embedding-distance distribution	✗
Pulse-PPG[16]	- / 50Hz, resample	[1D ResNet-26 Encoder + Dilated CNN Cross-Attention Distance Function + PPG Motif-based Relative Ranking] + Two-Phase Self-Supervised Pretraining (Masked Reconstruction +	✓	✓	-	✗	-	✗	✗	Hardware, training time	✗	✗

		Relative Contrastive Learning)										

Abbreviations: CNN, convolutional neural network; ECG, electrocardiogram; FT, fine-tuning; LP, linear probing; Med-CPT, medical clinical prompt tuning; MLM, masked language modeling; MoE, mixture-of-experts; n/a, not available;Net1D, 1D RegNet-based CNN; PPG, photoplethysmography; RAG, retrieval-augmented generation; RLM, random lead masking; SimCLR, simple contrastive learning of representations; SimSiam, simple siamese contrastive framework; SQI, signal quality index; ST-ECGFormer, spatio-temporal ECG transformer; sVRI, stress-induced vascular response index; UniCL, unified contrastive learning; WCR, wav2vec 2.0 + CMSC + RLM hybrid objective

Table S8. Computational benchmarking specifications

	Component	Description
Hardware (Google Colab High-RAM instances, PyTorch 2.9.0)	A100	NVIDIA A100-SXM4-80GB, 80GB VRAM
	T4	NVIDIA Tesla T4, 16GB VRAM
	CPU	Intel Xeon @ 2.20GHz, 4 cores, 50GB RAM
Metrics	Parameters[a]	sum(p.numel() for p in model.parameters()); encoder only for ECG-text models
	FLOPs	Computed using thop library[b]; may undercount transformer attention modules
	Inference throughput	Samples/second over 50 forward passes (after 5 warm-up passes); batch size 32 (GPU) or 8 (CPU), reduced if memory-constrained; throughput calculated as: (batch_size / mean_inference_time) × 1000
	Training throughput[c]	Samples/second during forward + backward + optimizer step; 20 iterations; AdamW (lr=1e-4); BCE loss with single-output head for consistency
	Training memory	Peak GPU memory via torch.cuda.max_memory_allocated(); includes model weights, activations, and gradients
	Fine-tuning time estimate (hr)	ms_per_sample × 100,000 samples × 10 epochs / 3,600,000; assumes a representative fine-tuning scenario (100k training samples, 10 epochs) and does not account for data loading, validation, or early stopping.

[a] For ECG-text models (MERL, KED, ESI, MELP), parameter counts reflect the ECG encoder only
[b] The library thop does not fully account for matrix multiplications within nn.MultiheadAttention modules, and can potentially undercount transformer models. This does not impact empirically measured metrics (throughput, training time, memory), which capture all operations regardless of theoretical counting.
[c] Per-sample training time (ms/sample) computed as training_step_time / batch_size to enable fair comparison across different batch sizes.

The complete benchmarking code, model implementations, and results are available at: https://github.com/aramis00/ECGPPG_FM_dataset/ (Interactive results are at https://aramis00.github.io/ECGPPG_FM_dataset/)

Abbreviations: A100, NVIDIA A100 graphics processing unit; AdamW, Adam optimizer with decoupled weight decay; BCE, binary cross-entropy; CPU, central processing unit; ECG, electrocardiogram; FLOPs, floating-point operations; GB, gigabyte; GHz, gigahertz; GPU, graphics processing unit; hr, hour; lr, learning rate; ms, millisecond; RAM, random-access memory; T4, NVIDIA Tesla T4 graphics processing unit; VRAM, video random-access memory.

Table S9. Computational requirements of 12-lead ECG foundation models

Model	FM Type	Architecture	Params[a] ckpt/ bench/ paper (M)	GFLOPs	Inference throughput (samples/s)[b] A100 / T4 / CPU	Train Memory (GB)	Fine-tuning Time[c] (h)
HuBERT-ECG	ECG SSL	HuBERT	93.1 / 92.8 / 93.0	18.0	786 / 143 / 9	4.1	1.0
ECG-FM	ECG SSL	Wav2Vec2	90.9 / 90.4 / 90.9	53.8	275 / 52 / 4	9.8	2.8
DeepECG-SSL	ECG SSL	Wav2Vec2	90.9 / 90.4 / 90.4	26.9	520 / 104 / 8	6.1	1.6
ESI	ECG-text[e]	ConvNeXtV2	88.5 / 85.6 / 85.6	46.8	273 / 52 / 3	15.9	3.3
ECG-JEPA	ECG SSL	ViT	85.4 / 85.4 / NR	45.4	185 / 45 / 2	10.4	4.3
ST-MEM	ECG SSL	ViT	85.2 / 85.2 / NR	65.5	224 / 52 / 3	11.4	3.9
MELP	ECG-text[e]	Wav2Vec2	65.6 / 62.0 / NR	27.3	390 / 76 / 4	6.1	2.1
HeartLang	ECG SSL	ViT	44.6 / 47.7 / NR	9.9	586 / 119 / 7	4.9	1.7
ECGFounder	Supervised	CNN (RegNet)	30.9 / 30.8 / NR	2.3	2,256 / 277 / 33	2.5	0.4
KED	ECG-text[d]	xResNet101	7.9 / 7.9 / NR	1.2	2,388 / 1,571 / 66	1.1	0.5
MERL (Vit Tiny)	ECG-text[d]	ViT-Tiny	5.5 / 5.5 / NR	0.7	4,678 / 1,727 / 82	1.0	0.3
MERL (ResNet 18)	ECG-text[d]	ResNet18	3.8 / 3.8 / NR	3.5	9,616 / 863 / 50	1.3	0.1
CPC	ECG SSL[d]	Conv + S4	3.3 / 3.0 / 3.8	7.0	1,447 / 260 / 10	4.1	0.8
S4* (SL baseline)	Non-FM; Supervised	S4	2.2 / 2.2 / 2.2	1.1	6,256 / 1,309 / 53	1.1	0.1

[a] Parameter counts have been derived from checkpoint files directly and benchmarking script. Parameter counts may vary between benchmark code and checkpoint files due to differences in which components are included (Benchmarks instantiate models with specific configurations and typically count only the encoder/backbone, whereas checkpoint file may include other components such as heads and projectors).
[b]Hardware: A100 (80GB), T4 (16GB), CPU (Intel Xeon, 50GB RAM)
[c] Train Time: Estimated fine-tuning time for 100k samples × 10 epochs on A100
[d] ECG-text models: Parameter counts reflect ECG encoder only; text encoders are typically frozen during fine-tuning

Default batch size: 32 (GPU), 8 (CPU); but for memory-constrained configurations, batch size was progressively reduced (32 → 16 → 8 → 4 → 2 → 1) until successful execution. Further details on the benchmarking set up is provided in the Supplementary Table S8.

Abbreviations: A100, NVIDIA A100 graphics processing unit; CNN, convolutional neural network; Conv, convolutional layer; ConvNeXtV2, Convolutional Next version 2; CPU, central processing unit; CPC, contrastive predictive coding; ECG, electrocardiogram; FM, foundation model; GFLOPs, giga floating-point operations; GB, gigabyte; h, hour; HuBERT, hidden-unit bidirectional encoder representations from transformers; M, million; NR, not reported; Params, parameters; RegNet, regularized network; ResNet, residual network; S4, structured state-space sequence model; SL, supervised learning; SSL, self-supervised learning; T4, NVIDIA Tesla T4 graphics processing unit; ViT, vision transformer.

Table S10. Computational requirements of single-lead ECG and PPG foundation models

Model	FM Type	Architecture	Params[a] ckpt/ bench	GFLOPs	Inference throughput (samples/s) [b] A100 / T4 / CPU	Train Memory (GB)	Fine-tuning time[c] (h)
Single-lead ECG							
HeartBERT	ECG SSL	RoBERTa	83.5M / 83.5M	43.5	360 / 75 / 4	6.8	2.5
ECGFounder	ECG SSL	CNN (RegNet)	30.9M / 30.8M	2.3	2,238 / 277 / 39	2.4	0.4
ECG-PT	ECG SSL	GPT	0.44M / 0.4M	0.3	1,602 / 409 / 16	1.0	0.2
PPG							
PulsePPG	PPG SSL	ResNet1D	28.5M / 29.4M	55.5	1,180 / 102 / 4	4.7	0.8
PaPaGei-S	PPG SSL	ResNet1D-MoE	5.8M / 5.0M	0.2	5,414 / 4,357 / 283	0.2	0.4
PPG-PT	PPG SSL	GPT	0.44M / 0.4M	0.3	1,629 / 407 / 25	1.0	0.2

[a] Parameter counts have been derived from checkpoint files directly and benchmarking script. Parameter counts may vary between benchmark code and checkpoint files due to differences in which components are included (Benchmarks instantiate models with specific configurations and typically count only the encoder/backbone, whereas checkpoint file may include other components such as heads and projectors).
[b]Hardware: A100 (80GB), T4 (16GB), CPU (Intel Xeon, 50GB RAM)
[c] Train Time: Estimated fine-tuning time for 100k samples × 10 epochs on A100

Default batch size: 32 (GPU), 8 (CPU); but for memory-constrained configurations, batch size was progressively reduced (32 → 16 → 8 → 4 → 2 → 1) until successful execution. Further details on the benchmarking set up is provided in the Supplementary Table S8.

Abbreviations: A100, NVIDIA A100 graphics processing unit; bench, benchmarked model; ckpt, checkpoint model; CNN, convolutional neural network; CPU, central processing unit; ECG, electrocardiogram; FM, foundation model; GFLOPs, giga floating-point operations; GB, gigabyte; GPT, generative pretrained transformer; h, hour; M, million; MoE, mixture of experts; PaPaGei-S, PaPaGei-small; Params, parameters; PPG, photoplethysmography; RegNet, regularized network; ResNet1D, one-dimensional residual network; RoBERTa, robustly optimized bidirectional encoder representations from transformers; SSL, self-supervised learning; T4, NVIDIA Tesla T4 graphics processing unit.

Table S11. Comprehensive characterization of 12-lead ECG dataset: links, technical specifications, clinical metadata, and accessibility

Dataset[a]	Record (n)	Patient (n)	Year	Country (No. of sites)	Setting	Sample rate (Hz)	Time (sec)	No. of leads	Demographic/ clinical data	ECG label	Data type	Access
HEEDB[68,69] (Harvard-Emory ECG database)	11.7 M	2.1 M	1980s ~ ongoing	US (1 site)	Hospital diagnostic ECG	250, 500	10	12	Age, gender, death, race, ethnicity, marital status, religion, language, veteran status, gender, cause of death, education level, ICD-9/10 Dx. codes	ECG Dx. (Marquette 12SL codes, human-readable 12SL report), measurements (HR, PR, QRSD, QT, QTc, Pax, Rax, Tax)	wfdb	C
CODE[70] (Clinical outcomes in digital ECG) - CODE 15% [71] - CODE – TEST [72]	2.3 M (346 K CODE-15%)	1.7 M (234 K CODE-15%)	2010-2016	Brazil (multi-site)	Tele-health setting	400	7~10	12	Age, gender	1dAVb, RBBB, LBBB, sinus bradycardia, Afib, sinus tachycardia, normal_ecg, death, follow up time	hdf5	R (CODE 15%, O; CODE-test, O)
MIMIC-IV ECG[73]	800 K	161 K	2008-2019	US (1 site)	Hospital diagnostic ECG	500	10	12	Age, gender, race, language, ICD-9/10 Dx. codes, longitudinal laboratory measurements, drugs, procedures, vital signs, death during ED/ ICU admission	machine measurements (machine generated ECG Dx., bandwidth, filtering, p/qrs/t interval and axis)	wfdb	C
SNUH LYDUS -160K[74] -50K[75]	167 K/ 50 K	167 K/ 50 K	2010-2020	South Korea (1 site)	Hospital diagnostic ECG	500 / 100	10	12	Age, gender	ECG Dx (text, machine generated, expert reviewed), measurement (ventricular rate, atrial rate, qrs duration, pr/qt intervals, p/r/t axes)	npz	R (50K, O)
EchoNext[76]	100K	36.3K	2018-2022	US (1 site)	Hospital diagnostic ECG (Echo matched)	250	10	12	Age, sex, year, setting, race, previous ECG presence	11 labels derived from matched Echo (AR, MR, TR, PR, RV systolic function, pericardial effusion, AS, LVEF, interventricular septum thickness, posterior wall thickness, PASP, TR Max Velocity), ECG labels - ventricular rate, atrial rate, pr/qrs/qt duration & counts, r and t axis	npy	R
IKEM[77] (Institut klinické a experimentální medicíny)	98.1 K	30.3 K	n/a	Czech Republic (1 site)	Hospital diagnostic ECG	500	10	12	Age, gender, weight, height	ventricular_rate, atrial_rate	hdf5	O

Dataset	Record (n)	Patient (n)	Year	Country (No. of sites)	Setting	Sample rate (Hz)	Time (sec)	No. of leads	Demographic/ clinical data	ECG label	Data type	Access
UK Biobank[78]	91.1 K	82.7 K	2014-2024 (ongoing)	UK (multi-site)	Volunteered exams, diagnostic ECG	500	10	12	Age, gender, indices of deprivation, clinical, imaging, metabolomic, proteomic, genomic data, (can be linked to cancer and death registries, hospital admissions, and primary care records)	Ventricular rate, suspicious flag raised by device, p and qrs duration, automatic Dx. comments	xml	R
CSN[79] (Chapman Shaoxing and Ningbo)	45.2 K	45.2 K	2013-2018	China (2 sites)	Hospital diagnostic ECG	500	10	12	Age, gender	ECG Dx. (63 SNOMED CT std. - expert reviewed), ventricular rate, atrial rate, qrs duration and counts, r and t axis	wfdb	O
SPH[80,81] (Shandong Provincial Hospital)	25.8 K	25.7 K	2019-2020	China (1 site)	Hospital diagnostic ECG	500	10-60	12	Age, gender	ECG Dx.(AHA std. - 11 category, 44 statement, expert reviewed)	h5	O
PTB-XL[b] [82,83]/ PTB-XL+ [84,85] (Physikalisch-Technische Bundesanstalt XL)	21.8 K	18.9 K	1989-1996	Germany (multi-site)	Diagnostic ECG - NR-Schiller AG device use	500 or 1000	10-120	12	Age, gender, weight, height, site, device	ECG Dx. (SCP-ECG std. - 5 super/ 24 sub class; 71 statements; 44 Dx/19 form/12 rhythm); expert annotated or machine generated; AHA std.) - PTB-XL+: added algorithm extracted ECG features, median beats, fiducial points, SNOMED-CT std.	wfdb	O
ZZU pECG[86,87] (Zhengzhou University pediatric ECG)	14.2 K	11.6 K	2018-2024	China (1 site)	Hospital diagnostic ECG, pediatrics (0-14 y.o.)	500	5-120	12 or 9	Age, gender, ICD-10 Dx. codes	ECG Dx.(64 AHA std., CHN std.; expert reviewed)	wfdb	O
Georgia[b] [88,89]	10.3 K	10.2 K	n/a	US (1 site)	Hospital diagnostic ECG	500	10	12	Age, gender	SNOMED CT std.	wfdb	O
CPSC 2018, CPSC 2018 extra[a] [88,89] (=ICBEB)	10.3 K	9.5 K	n/a	China (11 site)	Hospital diagnostic ECG	500	6–60	12	Age, gender, diagnosis	SNOMED CT std. (CPSC 2018 - 9 Dx.)	wfdb	O
SaMi-Trop[90,91]	2.0 K	1.6 K	2013-2016	Brazil (multi-site)	Chagas cohort	400	10	12	Age, gender, death, time to death	ECG Dx. - normal or not	hdf5	O

Dataset	Record (n)	Patient (n)	Year	Country (No. of sites)	Setting	Sample rate (Hz)	Time (sec)	No. of leads	Demographic/ clinical data	ECG label	Data type	Access
Pre-/Post-STEMI ECG Database, University of Michigan[92]	266	266	2016-2021	US (1 site)	Hospital diagnostic ECG, STEMI cohort	500	10	12	Age, gender, diabetes, hypertension, smoking, cerebrovascular disease, HF onset, death, death time	ECG label - Pre-STEMI or Post-STEMI (within 1week pre- and post-event; time of ECG recorded)	csv	O

[a]Access: O, open access; R, restricted access requiring registration and/or dataset-specific application, data use agreement (DUA), or material transfer agreement (MTA); C, credentialed access requiring approval for clinical/health data access, typically including data privacy/human-subjects training and a DUA.

[b] CPSC_2018, CPSC_2018 extra, INCART, PTB-XL, GEORGIA is part of the The PhysioNet/Computing in Cardiology Challenge 2020 dataset.

Abbreviations: Afib, atrial fibrillation; AHA, American Heart Association; CHN, Chinese Society of Cardiology standard; CSN, Chapman-Shaoxing and Ningbo; CPSC, China Physiological Signal Challenge; Dx., diagnosis; ED, emergency department; HF, heart failure; HR, heart rate; ICD-9/10, International Classification of Diseases, 9th/10th revision; n/a, not available; O, open access; PR, PR interval; QTc, corrected QT interval; QRSD, QRS duration; R, restricted access; RBBB, right bundle branch block; LBBB, left bundle branch block; 1dAVb, first-degree atrioventricular block; SCP-ECG, Standard Communications Protocol for Computer-assisted Electrocardiography; SNOMED CT, Systematized Nomenclature of Medicine Clinical Terms; std., standard; STEMI, ST-elevation myocardial infarction; wfdb, waveform database format; y.o., years old.

Table S12. Comprehensive characterization of reduced lead ECG and PPG datasets: technical specifications, clinical metadata, and accessibility

Dataset	Record (n)	Patient (n)	Year	Country (No. of sites)	Setting (data: ECG and/or PPG)	Sample rate (Hz)	Time	No. of leads	Demographic/ clinical data	ECG/PPG label & other waveform data	Data type	Access
MIMIC-III Waveform Database[93]	67.8K (MIMIC-III matched subset; 22.3K)	30.0K (MIMIC-III matched subset; 10.3K)	2008-2014	US (1 site)	Telemetry/ clinical grade monitoring – ICU (ECG and PPG)	125	variable	2~3	Matched subset: Age, gender, height, weight, race, language, ICD-9/10 Dx. codes, longitudinal laboratory measurements, drugs, procedures, V/S, death during ED/ ICU admission	No individual beat/ rhythm annotation. Other waveforms present: ABP, capnography.	wfdb	O
WAVES[94,95]	550K (ECG), 510K (PPG)	50.4K	2008-2017	US (1 site)	Telemetry/ clinical grade monitoring – pediatric ICU (ECG and PPG)	125	variable (mean 7 hr)	n/a	Age, gender, monitor alarm, length of stay	No individual beat/ rhythm annotation. Other waveforms present: ABP, capnography.	csv	R
SCOPE[96]	4.5K	4.5K	2019-2023	South Korea (1 site)	Telemetry/ clinical grade monitoring – ICU (ECG and PPG)	500 (ECG), 125 (PPG)	24~48hrs (prior to event (cardiac arrest, discharge, death))	1 (lead II)	Age, gender, APACHE II, ICU type, LOS, post-ICU mortality, pre-ICU arret, DNR status, outcome event (cardiac arrest, death, discharge)	No individual beat/ rhythm annotation.	vital file	O
VitalDB[97,98]	6.4K	6.1K	2016-2017	South Korea (1 site)	Telemetry/ clinical grade monitoring - intraoperative (ECG and PPG)	500	variable (entire time monitored in OR)	2~3	Age, gender, height, weight, surgery related info, preoperative laboratory value, intraoperative medication data, anesthesia related data, perioperative procedure	No individual beat/ rhythm annotation. Other waveforms present: ABP, capnography, BIS, etc.	vital file	O
MOVER[99,100]	83.5K	58.8k	2015-2122	US (1 site)	Telemetry/ clinical grade monitoring - intraoperative (ECG and PPG)	180 or 300 (ECG), 100 (PPG)	variable	1	Age, gender, height, weight, surgery related info, preoperative laboratory value, intraoperative medication data, anesthesia type, in-hospital death, billing codes	No individual beat/ rhythm annotation. Other waveforms present: ABP	xml	O (currently N/A due to data revision)
MIT-BIH Arrhythmia[101]	48	47	1975-1979	US (1 site)	Ambulatory (ECG)	360	30 min	2 (mostly ML II, V1)	Age, gender, medication	Beat & rhythm annotations (beat-to-beat, expert reviewed), signal quality labels	wfdb	O

Dataset	Record (n)	Patient (n)	Year	Country (No. of sites)	Setting (data: ECG and/or PPG)	Sample rate (Hz)	Time	No. of leads	Demographic/ clinical data	ECG/PPG label & other waveform data	Data type	Access
Long-term ST[102]	86	80	n/a	Slovenia, Italy (multi-site)	Ambulatory - Holter (ECG)	250	21~24 hr	2~3	Cardiac history, Dx., symptoms, medications, treatment	ST changes (ischemic, axis-related non-ischemic, episodes of slow ST level drift), ECG record description	wfdb	O
European ST-T [103,104]	90	79	n/a	8 Europe countries (multi-site)	Ambulatory (ECG)	250	2 hr	2	Age, gender, medication	Beat & rhythm annotations (beat-to-beat, expert annotated), signal quality labels	wfdb	O
St Petersburg INCART[105]	75	32	n/a	Russia (1 site)	Ambulatory - Holter (ECG)	257	30 min	12	Age, gender, cardiac diagnosis	Beat annotation (human reviewed), ECG record description	wfdb	O
MIT-BIH Atrial fibrillation[106]	25	n/a	n/a	US (1 site)	Ambulatory - Holter (ECG)	250	10 hr	2	None	Beat & rhythm annotations (beat-to-beat, expert reviewed)	wfdb	O
Long term AF[107]	84	n/a	n/a	US (1 site)	Ambulatory - Holter (ECG)	128	24~25 hr	2	None	Beat & rhythm annotations (beat-to-beat, expert reviewed)	wfdb	O
IRIDIA-AF[108]	167	152 (all paroxysmal Afib)	2006-2017	Belgium (1 site)	Ambulatory - Holter (ECG)	200	19~95 hr (total 24M sec)	2 (I and II)	Age, gender, record start/end	Atrial fibrillation start/end annotation, RR interval	hdf5	O
CPSC 2021 Paroxysmal Afib [109]	1.4K	63	n/a	n/a (multi-site)	Ambulatory or wearable (ECG)	200	variable (mean 20 min)	12 (Holter), 3 (wearable)	Rhythm abnormality Dx. group (non-AF, paroxysmal AF, persistent AF)	Beat & rhythm annotations	wfdb	O
Icentia11k[110,111]	54K	11K	2017-2018	Canada (multi-site)	Ambulatory Icentia CardioSTAT (ECG)	250	70 min	1 (ML I)	None	Beat & rhythm annotation (expert reviewed)	wfdb	O
PhysioNet2017 AF[112]	8828	8528	n/a	n/a	Mobile device - AliveCor (ECG)	300	9~60 sec	1 (I)	None	Rhythm label – Afib, noisy, normal, other	matlab	O
CapnoBase[113]	42	42	n/a	Canada (1 site)	Telemetry/ clinical grade monitoring - introaoperative (ECG and PPG)	100	8 min	1	None	ECG R peak, PPG pulse peak label (expert reviewed) Other waveforms present: capnography	csv	R
MESA polysomnography [114,115]	2K	2K	2010-2013	US (multi-site)	Telemetry/ clinical grade monitoring - polysomnography (ECG and PPG)	256	variable (mean 10.6 h)	2	Age, gender, BMI, race, smoking, apnea-hypopnea index, arousal index, sleep scores and quality metrics	Sleep stage & event annotation (respiratory event, desaturation, arousal, limb event, etc) Additional waveforms: EEG, EMG	edf, xml	R

Dataset	Record (n)	Patient (n)	Year	Country (No. of sites)	Setting (data: ECG and/or PPG)	Sample rate (Hz)	Time	No. of leads	Demographic/ clinical data	ECG/PPG label & other waveform data	Data type	Access
SDB[116]	146	146 (pediatrics; 56 SDB, 90 NonSDB)	n/a	Canada (1 site)	Telemetry/ clinical grade monitoring - pediatrics (suspected sleep apnea) - polysomnography (ECG and PPG)	62.5	>3 hr	1	n/a	Apneas/hypopnea index (AHI), SpO2 (1Hz)	csv	O
NuMoM2b[117]	5337	3163 (pregnancy)	2011-2013	US (multi-site)	Telemetry/ clinical grade monitoring – home polysomnography	20 (ECG), 75(PPG)	>2hr	1	Age, gender (all female), race, gestational age, height, weight, BMI, visit (early, 6-15 wks gestation; late, 22-31 wks gestation)	Apneas/hypopnea index (AHI), central apnea index, hypopnea index, obstructive AHI (OAHI), HR, position, activity; Additional waveforms: SpO2 (3Hz), pulse (3Hz), respiratory channels (nasal pressure, airflow, snore, thorax/abdomen belt)	edf, xml	R
PPG-BP[118]	657 (3 segments/ patient)	219	n/a	China (1 site)	Telemetry/ clinical grade monitoring - 3 min measurement	1000	2.1 sec	1	Age, gender, height, weight, hypertension, cardiac disease	SBP, DBP, HR measurements matched to PPG segment	txt	O
PPG DaLiA[119,120]	15	15	n/a	Germany (1 site)	Wearable - usual daytime activity (ECG and PPG)	700 (ECG),64 (PPG)	~2.5 hr	1	Age, gender, height, weight, skin type, fitness	Activity: sitting, walking, cycling, driving, table soccer, lunch, office work, stairs, heart rate label. Additional waveforms: respiration, ACC, TEMP	pkl	O
WESAD[121,122]	15	15	n/a	Germany (1 site)	Wearable - induced emotion (ECG and PPG)	700 (ECG),64 (PPG)	2 hr	1	Self-reported emotion metrics	Emotional states Additional waveforms: respiration, ACC, TEMP, EMG	pkl	O
TROIKA[123,124] (= IEEEPPG)	12	12 (all male)	n/a	China (1 site)	Wearable - treadmill (ECG and PPG)	125	5 min	1	Age, gender, height, weight, health status	SBP, DBP Additional waveforms: ACC	mat	O
ECSMP[125]	89	89 (healthy)	2018	China (1 site)	Telemetry/ clinical grade monitoring + wearable (ECG holter, PPG wearable) - induced emotion + sleep ECG collected the night before (ECG, PPG)	512 (ECG, holter), 64 (PPG)		1	Age, gender; sleep-related: sleep time, sleep efficiency, apnea index, apnea type, questionnaire (emotion, sleep quality, depression), CANTAB cognitive test	Sleep stage (deep, light, REM) ; Additional waveforms: during emotion (neutral, fear, sad, happy, anger, disgust, fatigue) induction - BT (4Hz), EDA (electrodermal activity, 4Hz), ACC (32Hz), inter-beat-interval (from PPG), HR (1Hz, from PPG), EEG (250Hz)	csv	O

Abbreviations: ACC, accelerometer; AF, atrial fibrillation; ABP, arterial blood pressure; APACHE II, Acute Physiology and Chronic Health Evaluation II; BIS, bispectral index; BMI, body mass index; DBP, diastolic blood pressure; DNR, do-not-resuscitate; Dx., diagnosis; ED, emergency department; EEG, electroencephalogram; ECG, electrocardiogram; EMG, electromyogram; ESI, European ST-T database; h, hour; hr, hour; ICU, intensive care unit; K, thousand; LOS, length of stay; M, million; min, minute; ML, modified lead; n/a, not available; No., number; NR, not reported; O, open access; OR, operating room; PPG, photoplethysmography; R, restricted access; SBP, systolic blood pressure; sec, second; TEMP, temperature; V/S, vital signs; wfdb, waveform database format; xml, extensible markup language.

Supplement References

1. Al-Masud, M., Alcaraz, J.M.L. & Strodthoff, N. Benchmarking ECG Foundational Models: A Reality Check Across Clinical Tasks. *arXiv preprint arXiv:2509.25095* (2025).
2. McKeen, K. *et al.* Ecg-fm: An open electrocardiogram foundation model. *JAMIA open* **8**, ooaf122 (2025).
3. Nolin-Lapalme, A. et al. Foundation models for electrocardiogram interpretation: clinical implications. *Eur. Heart J.* ehaf1119 (2026).
4. Coppola, E*., et al.* HuBERT-ECG as a self-supervised foundation model for broad and scalable cardiac applications. *medRxiv*, 2024.2011. 2014.24317328 (2024).
5. Na, Y., Park, M., Tae, Y. & Joo, S. Guiding masked representation learning to capture spatio-temporal relationship of electrocardiogram. *arXiv preprint arXiv:2402.09450* (2024).
6. Kim, S. Learning general representation of 12-lead electrocardiogram with a joint-embedding predictive architecture. *arXiv preprint arXiv:2410.08559* (2024).
7. Jin, J*., et al.* Reading your heart: Learning ecg words and sentences via pre-training ecg language model. *arXiv preprint arXiv:2502.10707* (2025).
8. Yu, H., Guo, P. & Sano, A. Ecg semantic integrator (esi): A foundation ecg model pretrained with llm-enhanced cardiological text. *arXiv preprint arXiv:2405.19366* (2024).
9. Liu, C*., et al.* Zero-shot ecg classification with multimodal learning and test-time clinical knowledge enhancement. *arXiv preprint arXiv:2403.06659* (2024).
10. Wang, F., Xu, J. & Yu, L. From Token to Rhythm: A Multi-Scale Approach for ECG-Language Pretraining. *arXiv preprint arXiv:2506.21803* (2025).
11. Tian, Y*., et al.* Foundation model of ECG diagnosis: Diagnostics and explanations of any form and rhythm on ECG. *Cell Reports Medicine* **5**(2024).
12. Li, J*., et al.* An Electrocardiogram Foundation Model Built on over 10 Million Recordings. *Nejm Ai* **2**(2025).
13. Davies, H.J., Monsen, J. & Mandic, D.P. Interpretable pre-trained transformers for heart time-series data. *arXiv preprint arXiv:2407.20775* (2024).
14. Tahery, S., Akhlaghi, F.H. & Amirsoleimani, T. HeartBERT: A Self-Supervised ECG Embedding Model for Efficient and Effective Medical Signal Analysis. *arXiv preprint arXiv:2411.11896* (2024).
15. Pillai, A., Spathis, D., Kawsar, F. & Malekzadeh, M. PaPaGei: Open foundation models for optical physiological signals. *arXiv priprint arXiv:2410.20542* (2024). https://doi.org/10.48550/arXiv.2410.20542
16. Saha, M*., et al.* Pulse-PPG: An open-source field-trained PPG foundation model for wearable applications across lab and field settings. *arXiv preprint arXiv:2502.01108* (2025). https://doi.org/10.48550/arXiv.2502.01108
17. Khattak, G.R*., et al.* Contrasting by Augmented Patient Electrocardiograms to Learn Representations for a Foundation Model. *International Conference on Artificial Intelligence in Medicine*, 202-206 (2025). https://doi.org/10.1007/978-3-031-95841-0_38
18. Sharma, A., Yang, L., McLean, C.Y., Cosentino, J. & Hormozdiari, F.I. ECG-nest-FM: A frequency-focused ECG foundation model with nested embeddings. *ICLR 2025 Workshop on* (2025). https://openreview.net/forum?id=k4P5JXv69b

19. Zhang, S., *et al.* ECGFM: A foundation model for ECG analysis trained on a multi-center million-ECG dataset. *Inf. Fusion* **124**, 103363 (2025). http://dx.doi.org/10.1016/j.inffus.2025.103363
20. Hu, S.M., Barrios, J.P. & Tison, G.H. A deep foundation model for electrocardiogram interpretation: enabling rare disease detection through transfer learning. *European Heart Journal-Digital Health* **6**, 619-623 (2025). https://doi.org/10.1093/ehjdh/ztaf051
21. Kumar, S., *et al.* Contrastive Learning for Personalized Cardiovascular Risk Prediction from Multi-Lead ECG Signal. *2025 International Conference on Machine Learning and Autonomous Systems (ICMLAS)*, 918-927 (2025). https://doi.org/10.1109/ICMLAS64557.2025.10968709
22. Liu, W., Pan, S., Chang, S., Huang, Q. & Jiang, N. Self-supervised learning for Electrocardiogram classification using Lead Correlation and Decorrelation. *Appl. Soft Comput.* **172**, 112871 (2025). http://doi.org/10.1016/j.asoc.2025.112871
23. Liu, W., *et al.* Lead-fusion Barlow twins: A fused self-supervised learning method for multi-lead electrocardiograms. *Information Fusion* **114**, 102698 (2025). https://doi.org/10.1016/j.inffus.2024.102698
24. Liu, Z.-Y., *et al.* Universal representations in cardiovascular ECG assessment: A self-supervised learning approach. *Int. J. Med. Inform.* **195**, 105742 (2025). http://doi.org/10.1016/j.ijmedinf.2024.105742
25. Cai, M., Jiang, J., Huang, W., Liu, C. & Arcucci, R. SuPreME: A Supervised Pre-training Framework for Multimodal ECG Representation Learning. *arXiv preprint arXiv:2502.19668* (2025). https://doi.org/10.48550/arXiv.2502.19668
26. Chen, W., Wang, H., Zhang, L. & Zhang, M. Temporal and spatial self supervised learning methods for electrocardiograms. *Scientific Reports* **15**, 6029 (2025). https://doi.org/10.1038/s41598-025-90084-2
27. Wang, Y., *et al.* AnyECG: Foundational Models for Electrocardiogram Analysis. *arXiv preprint arXiv:2411.17711* (2024). https://doi.org/10.48550/arXiv.2411.17711
28. Liu, C., Wan, Z., Cheng, S., Zhang, M. & Arcucci, R. Etp: Learning transferable ecg representations via ecg-text pre-training. *ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 8230-8234 (2024). http://doi.org/10.1109/ICASSP48485.2024.10446742
29. Skorik, S., Avetisyan, A., Diatlinko, E., Mindiiarova, R. & Markin, Y. Transferring Knowledge from 12-lead to 1-lead ECGs via Contrastive Learning. *2024 IEEE 48th Annual Computers, Software, and Applications Conference (COMPSAC)*, 1825-1830 (2024). https://doi.org/10.1109/COMPSAC61105.2024.00288
30. Gündüzalp, D. & Zou, C. Combined Self-Supervised Learning for ECG Classification Based on the Classification Token. *2024 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI)*, 1-8 (2024). https://doi.org/10.1109/BHI62660.2024.10913542
31. Moody, J.B., *et al.* Self-supervised deep representation learning of a foundation transformer model enabling efficient ECG-based assessment of cardiac and coronary function with limited labels. *medRxiv* (2024). http://doi.org/10.1101/2023.10.25.23297552
32. Sawano, S., *et al.* Applying masked autoencoder-based self-supervised learning for high-capability vision transformers of electrocardiographies. *Plos one* **19**, e0307978 (2024). https://doi.org/10.1371/journal.pone.0307978

33. Song, J.*, et al.* Foundation models for ecg: Leveraging hybrid self-supervised learning for advanced cardiac diagnostics. *arXiv preprint arXiv:2407.07110* (2024). https://doi.org/10.48550/arXiv.2407.07110
34. Vaid, A.*, et al.* A foundational vision transformer improves diagnostic performance for electrocardiograms. *NPJ Digit. Med.* **6**, 108 (2023). http://dx.doi.org/10.1038/s41746-023-00840-9
35. Zhang, H.*, et al.* Maefe: Masked autoencoders family of electrocardiogram for self-supervised pretraining and transfer learning. *IEEE Transactions on Instrumentation and Measurement* **72**, 1-15 (2022). https://doi.org/10.1109/TIM.2022.3228267
36. Bo, J.Y., Huang, H.-W., Chan, A. & Traverso, G. Pretraining ecg data with adversarial masking improves model generalizability for data-scarce tasks. *arXiv preprint arXiv:2211.07889* (2022). https://doi.org/10.48550/arXiv.2211.07889
37. Zhang, W., Yang, L., Geng, S. & Hong, S. Self-supervised time series representation learning via cross reconstruction transformer. *IEEE Transactions on Neural Networks and Learning Systems* (2023). https://doi.org/10.1109/TNNLS.2023.3292066
38. Wei, C.T., Hsieh, M.-E., Liu, C.-L. & Tseng, V.S. Contrastive heartbeats: Contrastive learning for self-supervised ecg representation and phenotyping. *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 1126-1130 (2022). https://doi.org/10.1109/ICASSP43922.2022.9746887
39. Li, F., Chang, H., Jiang, M. & Su, Y. A contrastive learning framework for ecg anomaly detection. *2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP)*, 673-677 (2022). https://doi.org/10.1109/ICSP54964.2022.9778634
40. Oh, J., Chung, H., Kwon, J.-m., Hong, D.-g. & Choi, E. Lead-agnostic self-supervised learning for local and global representations of electrocardiogram. *Conference on Health, Inference, and Learning*, 338-353 (2022). https://proceedings.mlr.press/v174/oh22a.html
41. Mehari, T. & Strodthoff, N. Self-supervised representation learning from 12-lead ECG data. *Computers in biology and medicine* **141**, 105114 (2022). https://doi.org/10.1016/j.compbiomed.2021.105114
42. Ma, C.*, et al.* An atrial fibrillation detection strategy based on self-supervised pre-training in wearable ECG monitoring. *IEEE Transactions on Instrumentation and Measurement* (2025). https://doi.org/10.1109/TIM.2025.3546413
43. Gu, X.*, et al.* Sensing cardiac health across scenarios and devices: A multi-modal foundation model pretrained on heterogeneous data from 1.7 million individuals. *arXiv preprint arXiv:2507.01045* (2025). https://doi.org/10.48550/arXiv.2507.01045
44. Li, H.*, et al.* MIRA: Medical Time Series Foundation Model for Real-World Health Data. *arXiv preprint arXiv:2506.07584* (2025).
45. Tudjarski, S., Gusev, M. & Kanoulas, E. Transformer-based heart language model with electrocardiogram annotations. *Sci. Rep.* **15**(2025). http://doi.org/10.1038/s41598-024-84270-x
46. Knight, E., Oikonomou, E.K., Aminorroaya, A., Pedroso, A.F. & Khera, R. Wearable-Echo-FM: An ECG-echo foundation model for single lead electrocardiography. *medRxiv* (2025). http://doi.org/10.1101/2025.06.10.25329163
47. Abbaspourazad, S.*, et al.* Large-scale training of foundation models for wearable biosignals. *arXiv preprint arXiv:2312.05409* (2023). https://doi.org/10.48550/arXiv.2312.05409

48. Kite, T., Siam, U.T., Ayers, B., Houstis, N. & Aguirre, A.D. Unlocking telemetry potential: Self-supervised learning for continuous clinical electrocardiogram monitoring. *arXiv preprint arXiv:2406.16915* (2024).
49. Luo, Y., Chen, Y., Salekin, A. & Rahman, T. Toward Foundation Model for Multivariate Wearable Sensing of Physiological Signals. *arXiv preprint arXiv:2412.09758* (2024).
50. Wang, G., Wang, Q., Nag, A. & John, D. A task-generic high-performance unsupervised pre-training framework for ECG. *IEEE Sens. J.* **24**, 21776-21785 (2024). http://doi.org/10.1109/JSEN.2024.3404141
51. Yu, H., Yang, H. & Sano, A. ECG-SL: Electrocardiogram (ECG) Segment Learning, a deep learning method for ECG signal. *arXiv preprint arXiv:2310.00818* (2023). https://doi.org/10.48550/arXiv.2310.00818
52. Xu, M.A., Moreno, A., Wei, H., Marlin, B.M. & Rehg, J.M. REBAR: Retrieval-Based Reconstruction for time-series contrastive learning. *arXiv preprint arXiv:2311.00519* (2023). https://doi.org/10.48550/arXiv.2311.00519
53. Guo, Z.*, et al.* SiamAF: learning shared information from ECG and PPG signals for robust atrial fibrillation detection. *arXiv preprint arXiv:2310.09203* (2023). https://doi.org/10.48550/arXiv.2310.09203
54. Li, Y.*, et al.* Cross-Granular Collaborative Recognition of Cortical Arousal and Sleep Stages From Photoplethysmography. *IEEE Trans. Biomed. Eng.* **72**, 1800-1810 (2025). http://doi.org/10.1109/tbme.2024.3523044
55. Chen, Z.*, et al.* GPT-PPG: a GPT-based foundation model for photoplethysmography signals. *Physiol. Meas.* **46**(2025). https://doi.org/10.48550/arXiv.2503.08015
56. Kazemi, K., Azimi, I., Liljeberg, P. & Rahmani, A.M. Respiration Rate estimation via smartwatch-based photoplethysmography and accelerometer data: A transfer learning approach. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **9**, 1-24 (2025). http://doi.org/10.1145/3712280
57. Xu, M.A.*, et al.* LSM-2: Learning from Incomplete Wearable Sensor Data. *arXiv preprint arXiv:2506.05321* (2025).
58. Liu, R.*, et al.* PhysCL: Knowledge-Aware Contrastive Learning of Physiological Signal Models for Cuff-Less Blood Pressure Estimation. *IEEE J. Biomed. Health Inform.* **29**, 4728-4740 (2025). http://doi.org/10.1109/jbhi.2025.3554495
59. Wu, H., Hu, Q., Wang, D., Zhu, S. & Yang, C. Enhancing atrial fibrillation detection in PPG analysis with sparse labels through contrastive learning. *Comput. Methods Programs Biomed.* **264**, 108698 (2025). http://doi.org/10.1016/j.cmpb.2025.108698
60. Benfenati, L.*, et al.* EnhancePPG: Improving PPG-based heart rate estimation with self-supervision and augmentation. *arXiv preprint arXiv:2412.17860* (2024). https://doi.org/10.48550/arXiv.2412.17860
61. Le, T.-D., Macabiau, C., Albert, K., Jouvet, P. & Noumeir, R. A Novel Transformer-Based Self-Supervised Learning Method to Enhance Photoplethysmogram Signal Artifact Detection. *IEEE Access* **12**, 159860-159874 (2024). http://doi.org/10.1109/ACCESS.2024.3488595
62. Narayanswamy, G.*, et al.* Scaling wearable foundation models. *arXiv preprint arXiv:2410.13638* (2024).
63. Yun, T.*, et al.* Unsupervised representation learning on high-dimensional clinical data improves genomic discovery and prediction. *Nat Genet* **56**, 1604-1613 (2024).

64. Ding, C., *et al.* SiamQuality: a ConvNet-based foundation model for photoplethysmography signals. *Physiol. Meas.* **45**, 085004 (2024). http://doi.org/10.1088/1361-6579/ad6747
65. Zhang, Z., *et al.* A general framework for generative self-supervised learning in non-invasive estimation of physiological parameters using photoplethysmography. *Biomed. Signal Process. Control* **98**, 106788 (2024). http://doi.org/10.1016/j.bspc.2024.106788
66. Mwaniki, P., *et al.* Using self-supervised feature learning to improve the use of pulse oximeter signals to predict paediatric hospitalization. *Wellcome Open Res.* **6**, 248 (2021). http://doi.org/10.12688/wellcomeopenres.17148.2
67. Ghorbani, R., Reinders, M.J. & Tax, D.M. Self-supervised ppg representation learning shows high inter-subject variability. *Proceedings of the 2023 8th International Conference on Machine Learning Technologies*, 127-132 (2023). https://doi.org/10.1016/j.bspc.2024.106216
68. Koscova, Z., *et al.* The Harvard-Emory ECG Database. *medRxiv*, 2024.2009. 2027.24314503 (2024).
69. Koscova, Z., *et al.* Harvard-Emory ECG database. (Data Science Platform, BDSP, 2025). https://doi.org/10.60508/rv6h-7d10
70. Ribeiro, A.H., *et al.* Automatic diagnosis of the 12-lead ECG using a deep neural network. *Nat Commun* **11**, 1760 (2020). https://doi.org/10.1038/s41467-020-15432-4
71. Ribeiro, A.H., *et al.* CODE-15%: a large scale annotated dataset of 12-lead ECGs, June 2021. Vol. 4916206 (Zenodo, 2021). http://doi.org/10.5281/zenodo.4916206
72. Ribeiro, A., *et al.* CODE-test: Annotated 12-lead ECG dataset. Vol. 1 (Zenodo, 2020). http://doi.org/10.5281/zenodo.3765780
73. Gow, B., *et al.* Mimic-iv-ecg: Diagnostic electrocardiogram matched subset. in *PhysioNet* (2023). https://doi.org/10.13026/4nqg-sb35
74. SNUH. SNUH LYDUS ECG 160K. (Korea Health Data Platform, KHDP, 2025). https://khdp.net/database/data-search-detail/402/LYDUS-SNUH-ECG-160K/1.0.0
75. SNUH. SNUH LYDUS ECG 50K. (Korea Health Data Platform, KHDP, 2025). https://khdp.net/database/data-search-detail/704/LYDUS-SNUH-ECG-50K/1.1.1
76. Elias, P. & Finer, J. Echonext: A dataset for detecting echocardiogram-confirmed structural heart disease from ecgs. (PhysioNet, 2025).
77. Seják, M., Sido, J. & Žahour, D. IKEM dataset v1.0.0. (Zenodo, 2023). https://doi.org/10.5281/zenodo.8393007
78. UK Biobank. (2024). https://www.ukbiobank.ac.uk/
79. Zheng, J., Guo, H. & Chu, H. A large scale 12-lead electrocardiogram database for arrhythmia study. (PhysioNet, 2022). https://doi.org/10.13026/wgex-er52
80. Liu, H., et al. A large-scale multi-label 12-lead electrocardiogram database with standardized diagnostic statements. (figshare, 2022). https://doi.org/10.6084/m9.figshare.c.5779802.v1
81. Liu, H., et al. A large-scale multi-label 12-lead electrocardiogram database with standardized diagnostic statements. Sci. Data 9(2022). http://dx.doi.org/10.1038/s41597-022-01403-5
82. Wagner, P., et al. PTB-XL, a large publicly available electrocardiography dataset. Sci. Data 7, 154 (2020). http://dx.doi.org/10.1038/s41597-020-0495-6

83. Wagner, P., Strodthoff, N., Bousseljot, R.-D., Samek, W. & Schaeffter, T. PTB-XL, a large publicly available electrocardiography dataset. (PhysioNet, 2022). http://dx.doi.org/10.13026/6sec-a640
84. Strodthoff, N., et al. PTB-XL+, a comprehensive electrocardiographic feature dataset. (PhysioNet, 2023). https://physionet.org/content/ptb-xl-plus/1.0.1/
85. Strodthoff, N., et al. PTB-XL+, a comprehensive electrocardiographic feature dataset. Sci. Data 10, 279 (2023). http://dx.doi.org/10.1038/s41597-023-02153-8
86. Tan, J., et al. A pediatric ECG database with disease diagnosis covering 11643 children. Scientific Data 12, 867 (2025).
87. Jian, T., et al. A pediatric ECG database with disease diagnosis covering 11643 children. (figshare, 2025). https://doi.org/10.6084/m9.figshare.27078763
88. Perez Alday, E.A., et al. Classification of 12-lead ECGs: The PhysioNet/Computing in Cardiology Challenge 2020. (PhysioNet, 2022). https://doi.org/10.13026/dvyd-kd57
89. Perez Alday, E.A., et al. Classification of 12-lead ECGs: the PhysioNet/Computing in Cardiology Challenge 2020. Physiol. Meas. 41, 124003 (2021). http://doi.org/10.1088/1361-6579/abc960
90. Cardoso, C.S., et al. Longitudinal study of patients with chronic Chagas cardiomyopathy in Brazil (SaMi-Trop project): a cohort profile. BMJ Open 6, e011181 (2016). https://doi.org/10.1136/bmjopen-2016-011181
91. Ribeiro, A.L.P., et al. Sami-Trop: 12-lead ECG traces with age and mortality annotations. (Zenodo, 2021). https://doi.org/10.5281/zenodo.4905618
92. Asthana, V., et al. Pre-/Post-STEMI ECG Database. (University of Michigan - Deep Blue Data, 2024). https://doi.org/10.7302/gk9v-ka27
93. Moody, B., Moody, G., Villarroel, M., Clifford, G. & Silva, I. MIMIC-III Waveform Database Matched Subset. (PhysioNet, 2020). https://doi.org/10.13026/c2294b
94. Miller, D., Dhillon, G.S., Bambos, N., Shin, A. & Scheinker, D. WAVES – the Lucile Packard children's hospital pediatric physiological waveforms dataset. *Sci. Data* **10**(2023). http://dx.doi.org/10.1038/s41597-023-02037-x
95. Stanford, W.i. WAVES. (Redivis, 2021). http://dx.doi.org/10.57761/5tdn-yy04
96. SCOPE: A survival and cardiac arrest outcome dataset with PPG and ECG waveforms from intensive care units. (Korea Health Data Platform, KHDP, 2025). https://khdp.net/database/data-search-detail/698/icu-cardiac-arrest/1.0
97. Lee, H.-C.*, et al.* VitalDB, a high-fidelity multi-parameter vital signs database in surgical patients. *Sci. Data* **9**, 279 (2022). http://dx.doi.org/10.1038/s41597-022-01411-5
98. Lee, H.-C. & Jung, C.-W. VitalDB, a high-fidelity multi-parameter vital signs database in surgical patients. (PhysioNet, 2022). https://doi.org/10.13026/czw8-9p62
99. Samad, M.*, et al.* Medical Informatics Operating Room Vitals and Events Repository (MOVER): a public-access operating room database. *JAMIA Open* **6**, ooad084 (2023). https://doi.org/10.1093/jamiaopen/ooad084
100. Unknown. MOVER: Medical informatics operating room vitals and events repository. (UCI Machine Learning Repository, 2023). https://doi.org/10.24432/C5VS5G
101. Moody, G.B. & Mark, R.G. MIT-BIH Arrhythmia Database. (PhysioNet, 1992). https://doi.org/10.13026/C2F305
102. Jager, F.*, et al.* The Long-Term ST database. (PhysioNet, 1995). https://doi.org/10.13026/C2G01T

103. Taddei, A., *et al.* The European ST-T database: standard for evaluating systems for the analysis of ST-T changes in ambulatory electrocardiography. *Eur. Heart J.* **13**, 1164-1172 (1992). https://doi.org/10.1093/oxfordjournals.eurheartj.a060332
104. Taddei, A., *et al.* European ST-T database. (PhysioNet, 2000). https://doi.org/10.13026/C2D59Z
105. Tihonenko, V., Khaustov, A., Ivanov, S. & Rivin, A. St.-Petersburg institute of cardiological technics 12-lead arrhythmia database. (PhysioNet, 2007). https://doi.org/10.13026/C2V88N
106. Moody, G.B. & Mark, R.G. MIT-BIH Atrial Fibrillation Database. (PhysioNet, 1992). https://doi.org/10.13026/C2MW2D
107. Petrutiu, S., Sahakian, A.V. & Swiryn, S. The long-term AF database. (PhysioNet, 2003). https://doi.org/10.13026/C2QG6Q
108. Gilon, C., Grégoire, J.-M., Mathieu, M., Carlier, S. & Bersini, H. IRIDIA-AF, a large paroxysmal atrial fibrillation long-term electrocardiogram monitoring database. *Scientific data* **10**, 714 (2023).
109. Wang, X., *et al.* Paroxysmal atrial fibrillation events detection from dynamic ECG recordings: The 4th China Physiological Signal Challenge 2021. (PhysioNet, 2021). https://doi.org/10.13026/ksya-qw89
110. Tan, S., *et al.* Icentia11K: An unsupervised representation learning dataset for arrhythmia subtype discovery. *arXiv preprint arXiv:1910.09570* abs/1910.09570(2019). https://doi.org/10.48550/arXiv.1910.09570
111. Tan, S., *et al.* Icentia11k single lead continuous raw electrocardiogram dataset. (PhysioNet, 2022). https://doi.org/10.13026/kk0v-r952
112. Clifford, G.D., *et al.* AF classification from a short single lead ECG recording: The PhysioNet/computing in cardiology challenge 2017. in *2017 computing in cardiology (CinC)* 1-4 (IEEE, 2017).
113. Karlen, W. CapnoBase IEEE TBME Respiratory Rate Benchmark. (Borealis, 2021). https://doi.org/10.5683/SP2/NLB8IT
114. Chen, X., *et al.* Racial/ethnic differences in sleep disturbances: The Multi-Ethnic Study of atherosclerosis (MESA). *Sleep* **38**, 877-888 (2015). https://dx.doi.org/10.5665/sleep.4732
115. National Sleep Research, R. Multi-ethnic study of atherosclerosis (MESA). (National Sleep Research Resource, NSRR, 2016). https://doi.org/10.25822/n7hq-c406
116. Garde, A., *et al.* Development of a screening tool for sleep disordered breathing in children using the phone Oximeter™. *PloS one* **9**, e112959 (2014). https://figshare.com/articles/dataset/Development_of_a_Screening_Tool_for_Sleep_Disordered_Breathing_in_Children_Using_the_Phone_Oximeter/1209662
117. Facco, F.L., *et al.* NuMoM2b Sleep-Disordered Breathing study: objectives and methods. *American journal of obstetrics and gynecology* **212**, 542. e541-542. e127 (2015).
118. Liang, Y., Liu, G., Chen, Z. & Elgendi, M. PPG-BP Database. (figshare, 2022). https://doi.org/10.6084/m9.figshare.5459299.v5
119. Schmidt, A.R.I.I. PPG-DaLiA. (UCI Machine Learning Repository, 2019). https://doi.org/10.24432/C53890
120. Reiss, A., Indlekofer, I., Schmidt, P. & Van Laerhoven, K. Deep PPG: Large-scale heart rate estimation with convolutional neural networks. *Sensors (Basel)* **19**, 3079 (2019). http://doi.org/10.3390/s19143079

121. Philip Schmidt, A.R. WESAD (Wearable Stress and Affect Detection). (UCI Machine Learning Repository, 2018). https://doi.org/10.24432/C57K5T
122. Schmidt, P., Reiss, A., Duerichen, R., Marberger, C. & Van Laerhoven, K. Introducing WESAD, a multimodal dataset for wearable stress and affect detection. *Proceedings of the 20th ACM International Conference on Multimodal Interaction*, 400-408 (2018). http://doi.org/10.1145/3242969.3242985
123. Chang Wei Tan, Christoph Bergmeir, Francois Petitjean & Webb, G.I. IEEEPPG dataset. (zenodo, 2020). https://doi.org/10.5281/zenodo.3902710
124. Zhang, Z., Pi, Z. & Liu, B. TROIKA: a general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise. *IEEE Trans. Biomed. Eng.* **62**, 522-531 (2015). http://doi.org/10.1109/TBME.2014.2359372
125. Gao, Z., Cui, X., Wan, W., Zheng, W. & Gu, Z. ECSMP: A dataset on emotion, cognition, sleep, and multi-model physiological signals. *Data in Brief* **39**, 107660 (2021).