DeepECG: From Code to Clinic – Building Trustworthy, Scalable AI for Cardiovascular Care

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PROGRAM DISCLOSURE OF COMMERCIAL SUPPORT

Nature of Relationship	Name of the for-profit of not-for-profit organization	Description of Relationship
Any direct financial payments including receipt of honoraria	Boehringer Ingelheim Biotronic Servier Abbott Society for Cardiovascular Angiography & Interventions	Speaker fees
Membership on advisory boards or speakers' bureaus	Pillow Health Canada (FrontRx)	Director
Funded grants of clinical trials	Quebec Health Research Fund (FRQS) Montreal Heart Institute Research Center University of Montreal Canadian Institute for Advanced Research (CIFAR) IVADO	Research Grants
Patents on a drug, product or device	R31-07141.PRO METHOD AND SYSTEM FOR ASSESSMENT OF VENTRICULAR EJECTION - FRACTION	Patent - Owner
All other investments/relationship that could be seen as having the potential to influence the content of the educational activity	None	None

Institut de Cardiologie de Montréal (Montreal, Quebec, Canada)

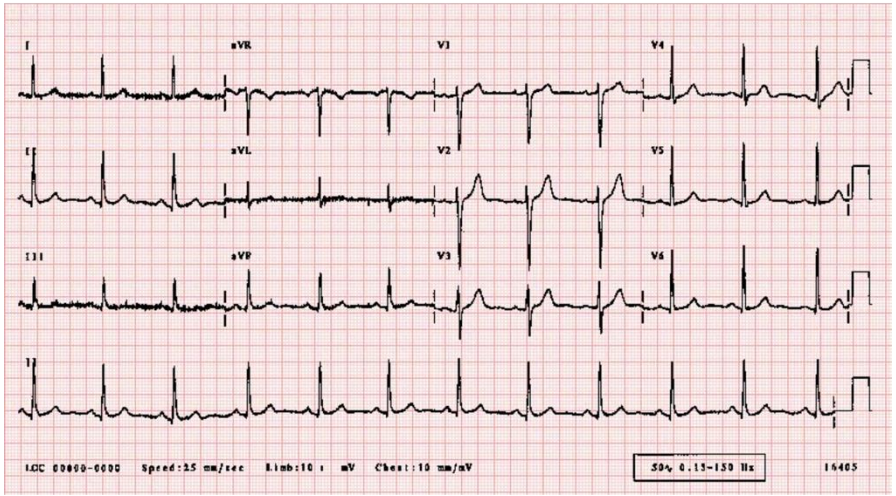
Outline

1. DeepECG Algorithm
2. DeepECG-AI Platform
3. HEART-AI Study
4. Cost-effectiveness
5. Energy Impact

What?
So what?
Why now?

What?

Key Problem and Approach



The 12-lead Electrocardiogram

The ECG is the most commonly perform cardiovascular test

Performed over 400 million times a year in the U.S. alone

Used to detect arrythmias, ischemic coronary disease

With AI, **additional disease states** can be detected as part of opportunistic screening (and AI often outperforms The cardiologist)

DeepECG-SL and DeepECG-SSL

Alexis Nolin-Lapalme[1,2,3,4*], Achille Sowa[1,2,4*], Jacques Delfrate[2,4], Olivier Tastet[2], Denis Corbin[2], Merve Kulbay[2], Derman Ozdemir[2,14], Marie-Jeanne Noël[2], Surbhi Sharma[5], Minhaj Ansari[6], I-Min Chiu[7], Valentina Dsouza[13], Sam F. Friedman[13], Jonathan Afilalo[9], Sushravya Raghunath[10], Michael Chassé[11], Brian Potter[11], Pierre Adil Elias[10], Gilbert Jabbour[2], Mourad Bahani[2], Marie-Pierre Dubé[2], Patrick M. Boyle[5], Neal A. Chatterjee[5], Joshua Barrios[6], Geoffrey H. Tison[6], David Ouyang[7], Mahnaz Maddah[13], Shaan Khurshid[8,11,12], Julia Cadrin-Tourigny[2], Rafik Tadros[2], Julie Hussin[1, 2, 3], Robert Avram[1, 2, 4, †].

Key Problem and Approach

Current ECG-AI Limitations

Lack of **generalizability** across diverse populations

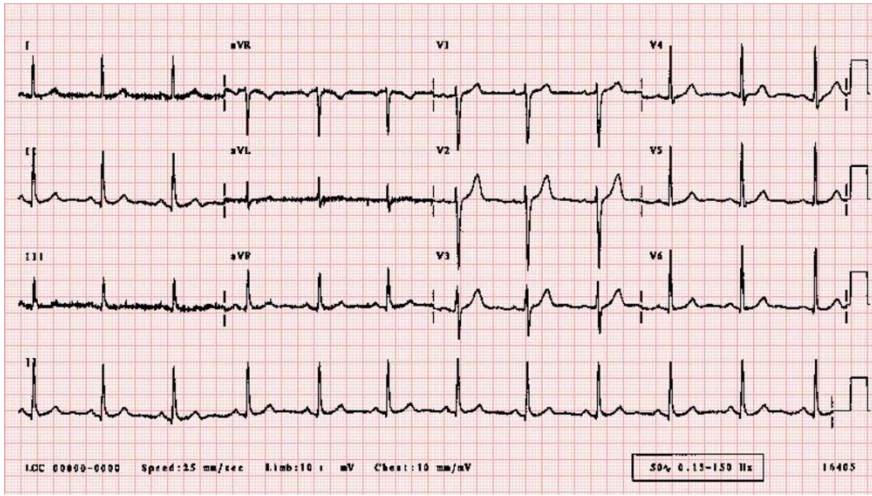
Reliance on **closed-source** models limiting research and improvement

Struggles with **limited labeled** data for rare conditions

Our Approach

DeepECG-SL (Supervised Learning): Trained on 1M+ labeled ECGs for 77 diagnostic tasks

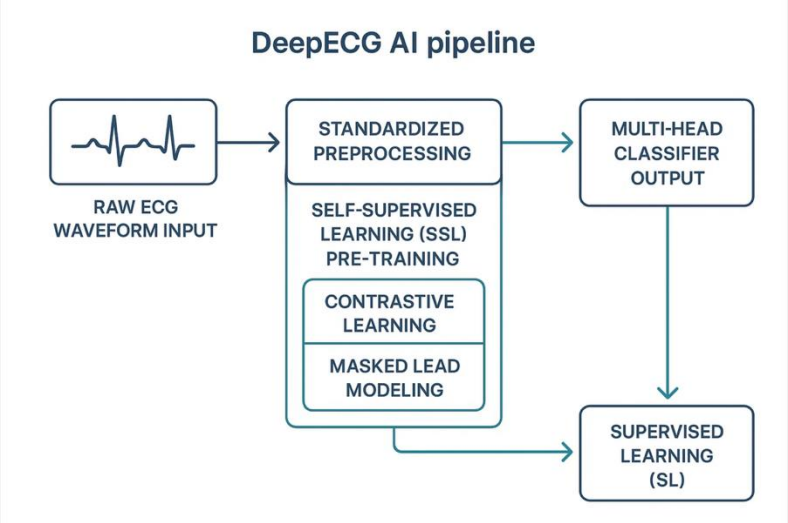
DeepECG-SSL (Self-Supervised Learning): Pretrained on 1.9M unlabeled ECGs + fine-tuned for specific tasks



Model Comparison

Feature	DeepECG-SL	DeepECG-SSL
Size	60x smaller	Larger
Speed	27x faster	More compute-intensive
Best for	Resource-limited settings	Rare conditions, biomarkers
Training data	Labeled ECGs	Unlabeled + labeled ECGs

Tech Stack & Data Pipeline



Self-supervised vs Supervised

DeepECG-SSL uses **contrastive learning** and **masked-lead modeling** for pre-training, while DeepECG-SL uses traditional supervised learning

Standardized Preprocessing

Unified pipeline ensures consistent signal processing across all ECG sources

Auto-label Extraction

Automated extraction from free-text ECG reports → 77 cardiac conditions

Deployment Ready

Code + weights on GitHub; Docker image drops into any EMR system

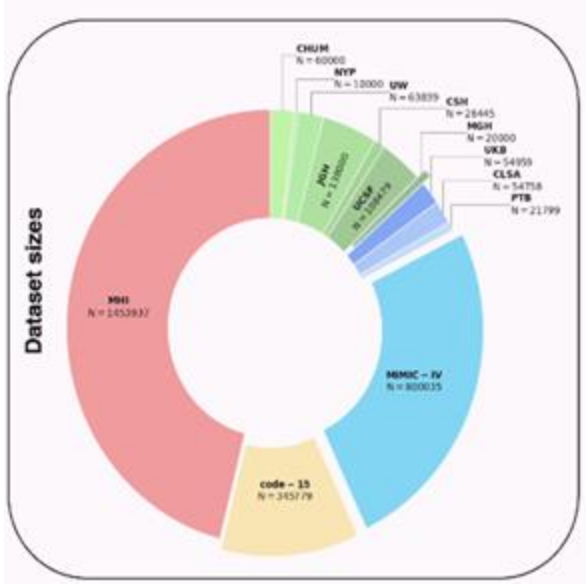
Validation performed in eleven datasets

4 External Public Datasets (EPD) :

MIMIC-IV, CLSA, UKB, PTB

7 External Private Healthcare Datasets (EHD):

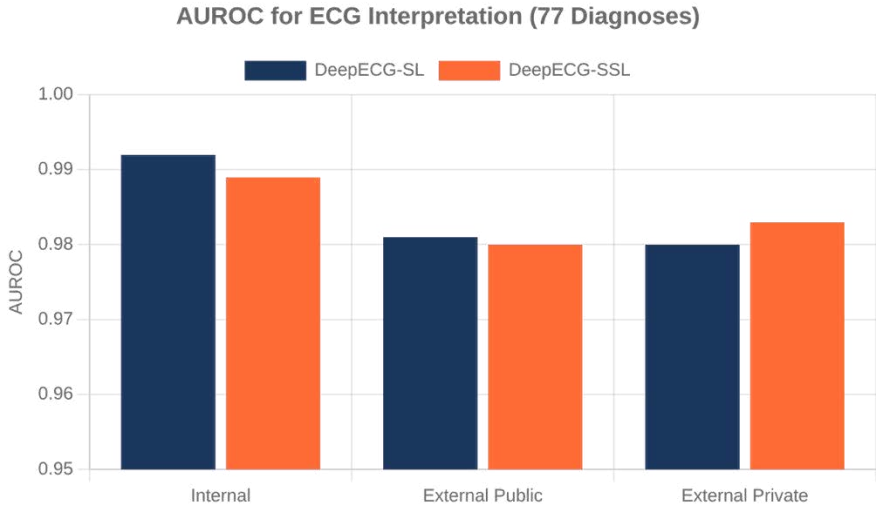
University of California (San Francisco), Cedars-Sinai, New York Presbyterian, University of Washington, Massachusetts General Hospital and Jewish General Hospital, Montreal University Center (CHUM)



Validation Scale

Development Cohort	External Validation
145,323	**109,870+**
Patients	Patients
669,782	**437,323+**
ECGs	ECGs

Both DeepECG-SL and DeepECG-SSL Generalize Well for ECG Interpretation



Key Findings

Both models achieve **AUROC > 0.98** for 77 diagnoses

Minimal performance degradation when tested on different healthcare systems

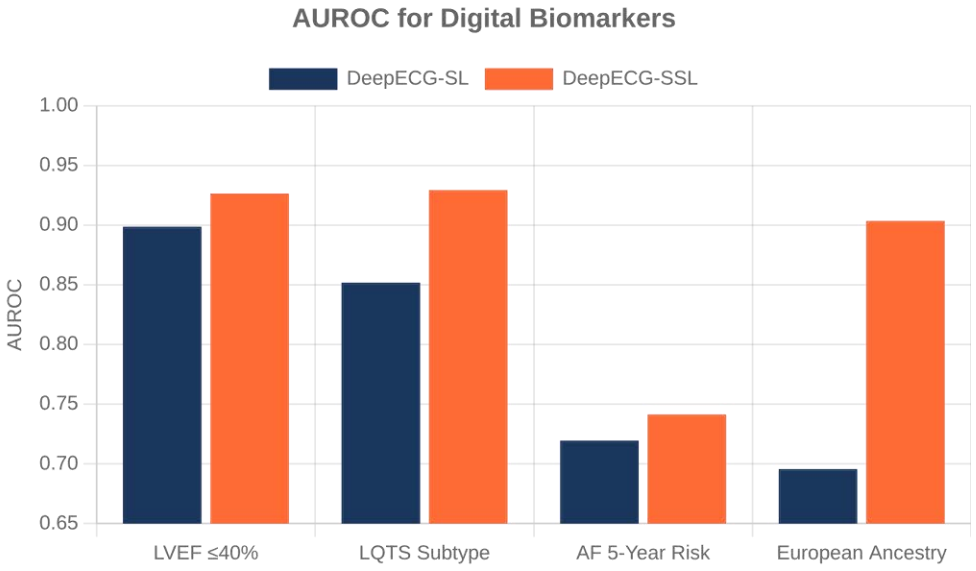
Implications

Both models are clinically viable for general ECG interpretation

DeepECG-SL offers efficiency advantages with minimal performance trade-off

Open-source nature enables widespread adoption and further improvement

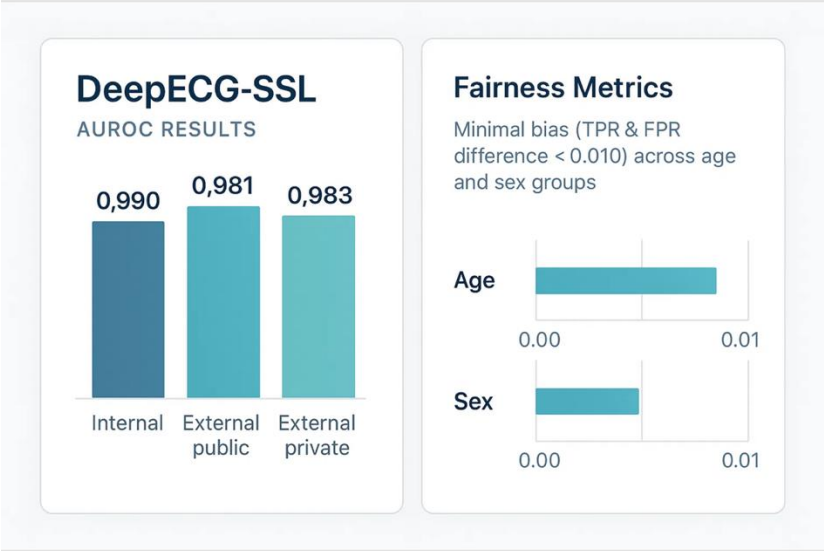
DeepECG-SSL Achieves Superior Performance for Digital Biomarkers and Rare Diseases



Performance Improvements with SSL

- LVEF ≤40% Prediction: **+0.028 AUROC** improvement
- LQTS Subtype Classification: **+0.078 AUROC** improvement
- AF 5-Year Risk Prediction: **+0.022 AUROC** improvement
- European Ancestry Detection: **+0.209 AUROC** improvement

Fairness: How equally the model performs across different groups



Key Findings

In this case, both bars are below 0.01 → **Model is fair** across age and sex.

DeepECG-ECHONeXT: Structural Heart Disease Detection

800,000

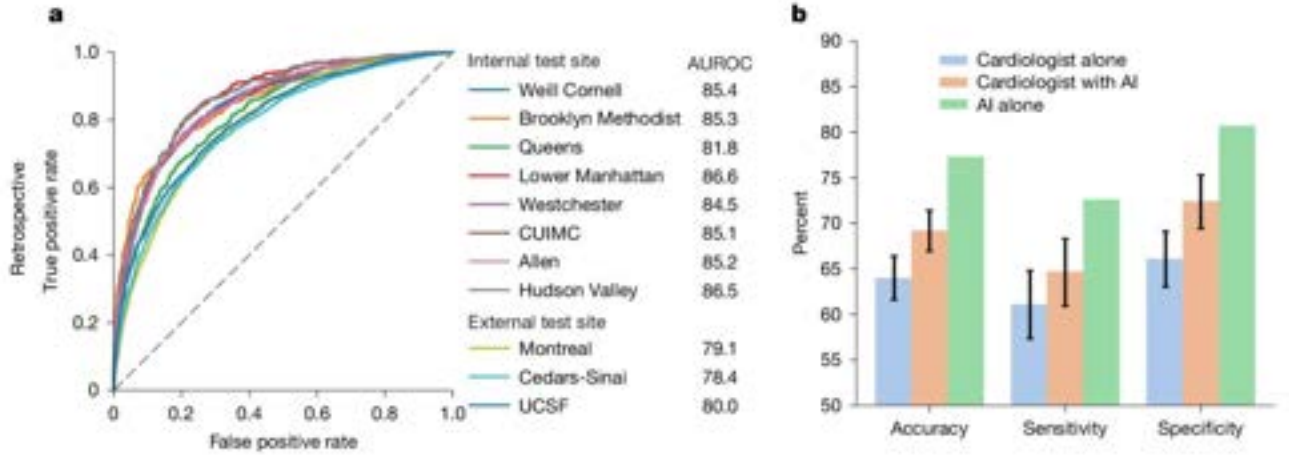
ECGs

150,000

Patients

0.80

AUROC at Montreal Heart Institute



Clinical Impact

Early detection of **structural heart disease (reduced EF, moderate valvular disease, pulmonary hypertension, left ventricular hypertrophy)** before symptoms develop

Potential to reduce morbidity and mortality through timely intervention

AI outperformed cardiologists + Cardiologists + AI

Poterucha et al. Nature. 2025. 10.1038/s41586-025-09227-0

So What?

So What?

SSL superior for RARE (n<10,000) conditions

State-of-the-art accuracy for rare conditions like LQTS and biomarker prediction tasks, leveraging unlabeled data to learn robust representations

DeepECG-SL: Optimized for Resource Constraints

60x smaller, 27x faster than SSL model—ideal for resource-limited settings while maintaining strong diagnostic performance in ECG interpretation

Clinical Relevance

Enables EXPERT level interpretation for ECG
Could enable earlier detection of certain “invisible to the human eye” like structural heart diseases

Open-Source Impact

Released weights, preprocessing tools, and validation code to accelerate research and clinical implementation worldwide
https://github.com/HeartWise-AI/DeepECG_Docker

Comparison to Prior Work

Outperforms ECG-FM [1] (SSL) in multi-label tasks; matches ECGFounder [2] (SL) with 10x less data

1. ECG-FM: McKeen, K. et al. ECG-FM: An Open Electrocardiogram Foundation Model. arXiv(2024).

2. ECGFounder: Li, J. et al. An Electrocardiogram Foundation Model Built on Over 10 Million Recordings. arXiv(2024).

Open weight models & paper

https://github.com/HeartWise-AI/DeepECG_Docker

Paper (Pre-print)

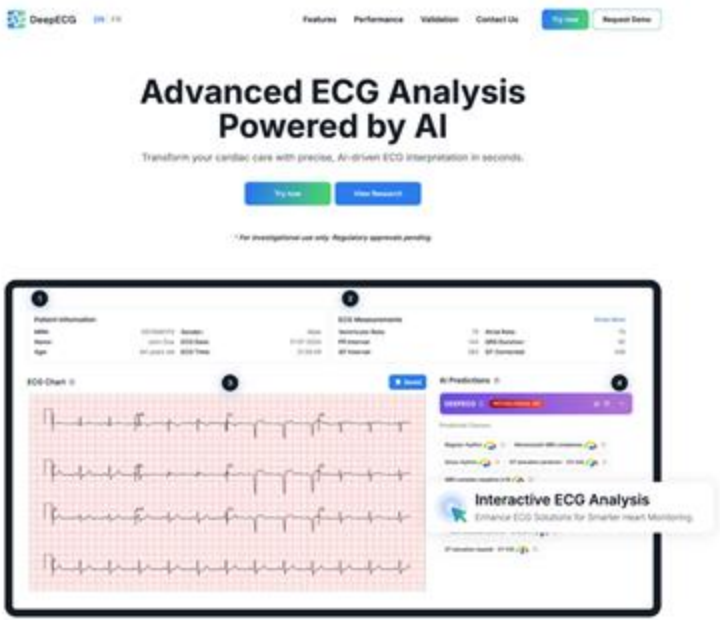
Why now?

DeepECG.AI platform and prospective implementation studies

HEART-AI

Olivier Tastet, Jacques Delfrate, Denis Corbin, Marie-Gabrielle Lessard, Alain Vadeboncoeur, Julia Cadrin-Tourigny, Rafik Tadros, Maxime Tremblay-Gravel, Anique Ducharme, Robert Avram

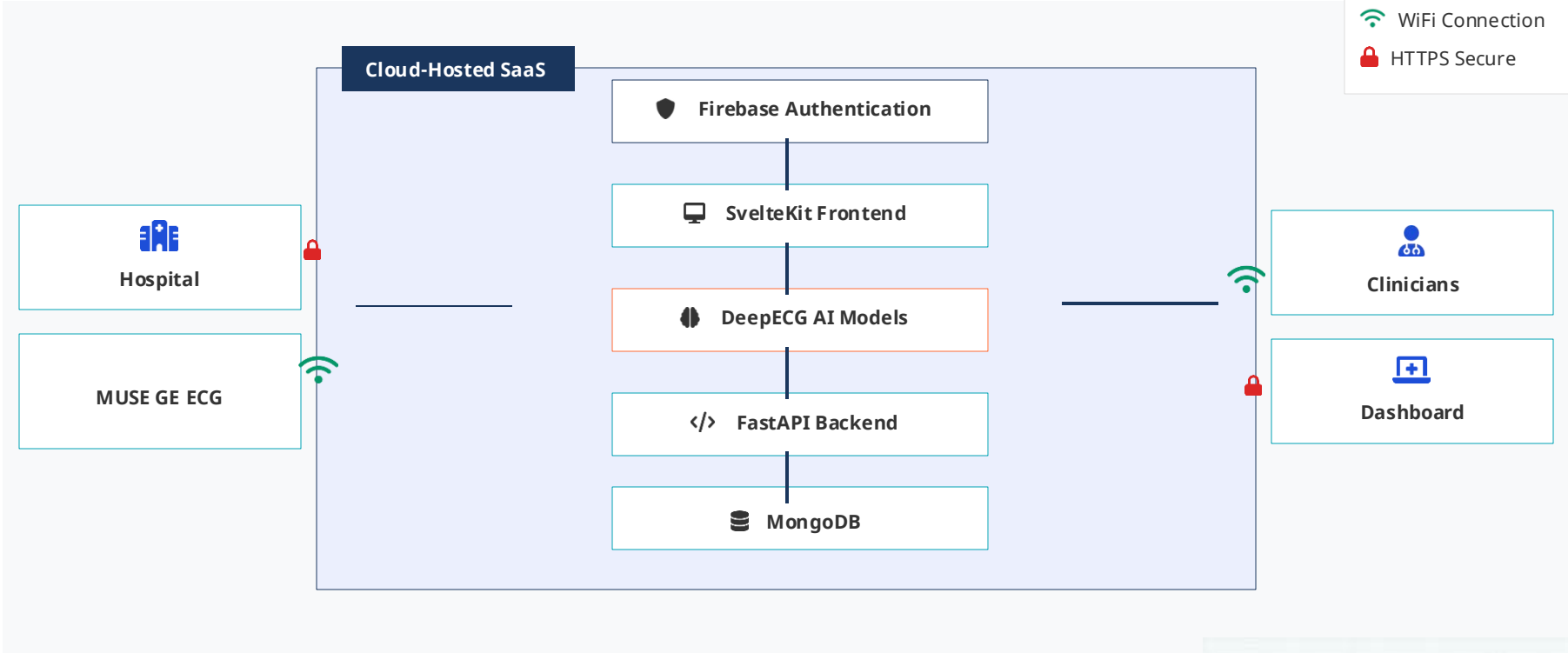
www.DeepECG.ai Platform



- Built by our team at **Montreal Heart Institute**
- Features:
  - Use of open-source and closed-source ECG-AI models
  - Consenting
  - Randomization
  - Audit trails
  - Compatible with General Electric © Machines (Wi-Fi enabled)

https://deepecg.ai/

DeepECG Platform Architecture



Data Acquisition

MUSE GE ECGs via WiFi

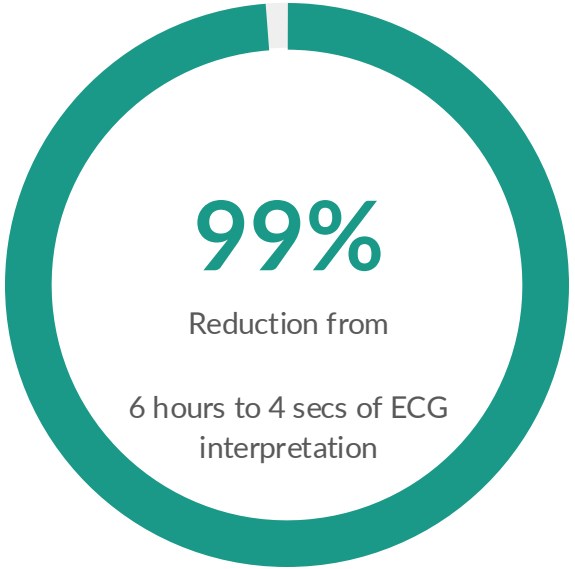
Processing

Cloud-hosted AI inference

Delivery

SaaS model with secure access

DeepECG.ai platform allows near real time expert level ECG diagnosis



HEART-AI TRIAL : Implementation of the DeepECG-SSL-ECHONeXT algorithm

NCT06462989

Clinical Challenge

Delayed diagnosis of **structural heart diseases** leads to increased morbidity/mortality
Resource strain on healthcare system

Current Crisis

43% increase in TTE referrals post-COVID
Wait times >90 days at major Canadian cardiac centers
No standardized prioritization system

Impact

SHD costs exceed $100B annually in US
6.4-10% of SHD cases remain undetected in population >65
Need for efficient diagnostic strategies

Research Question and Population

Can ECG-AI (ECHONeXT) with a recommendation to order a TTE and an associated priority increase rate of SHD diagnoses at 30 days?

Study Population & Design

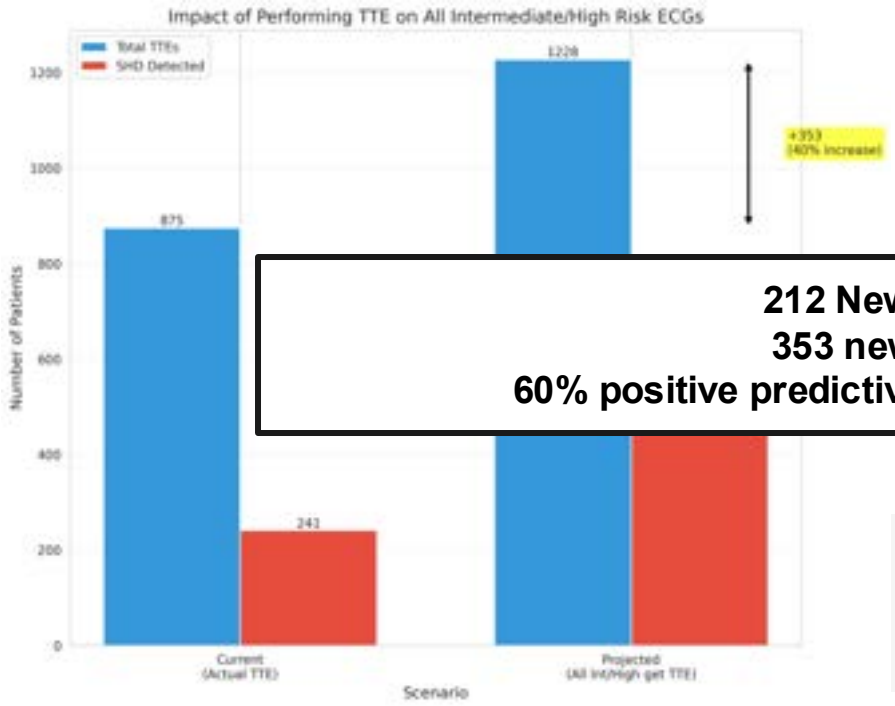
16,160 newly referred patients
Multi-center implementation
Pragmatic, open-label design

Intervention: ECHONeXT Risk Stratification

High Risk: Priority TTE within 1 month
Intermediate Risk: TTE within 1-3 months
Low Risk: Standard scheduling

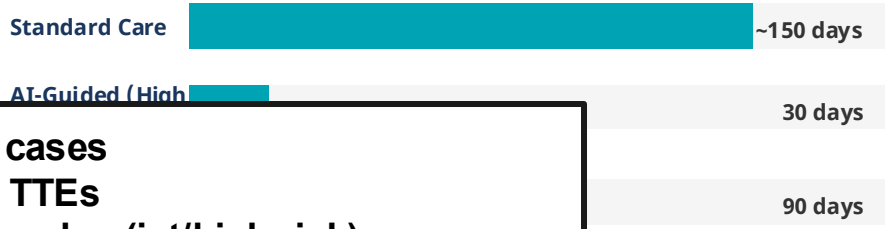
Primary Outcome: Rate of SHD diagnosis at 30 days.

HEART-AI PILOT STUDY RESULTS : 10000 patients screened with ECG-AI at MHI (2023-01 to 12)



212 New cases
353 new TTEs
60% positive predictive value (int/high risk)

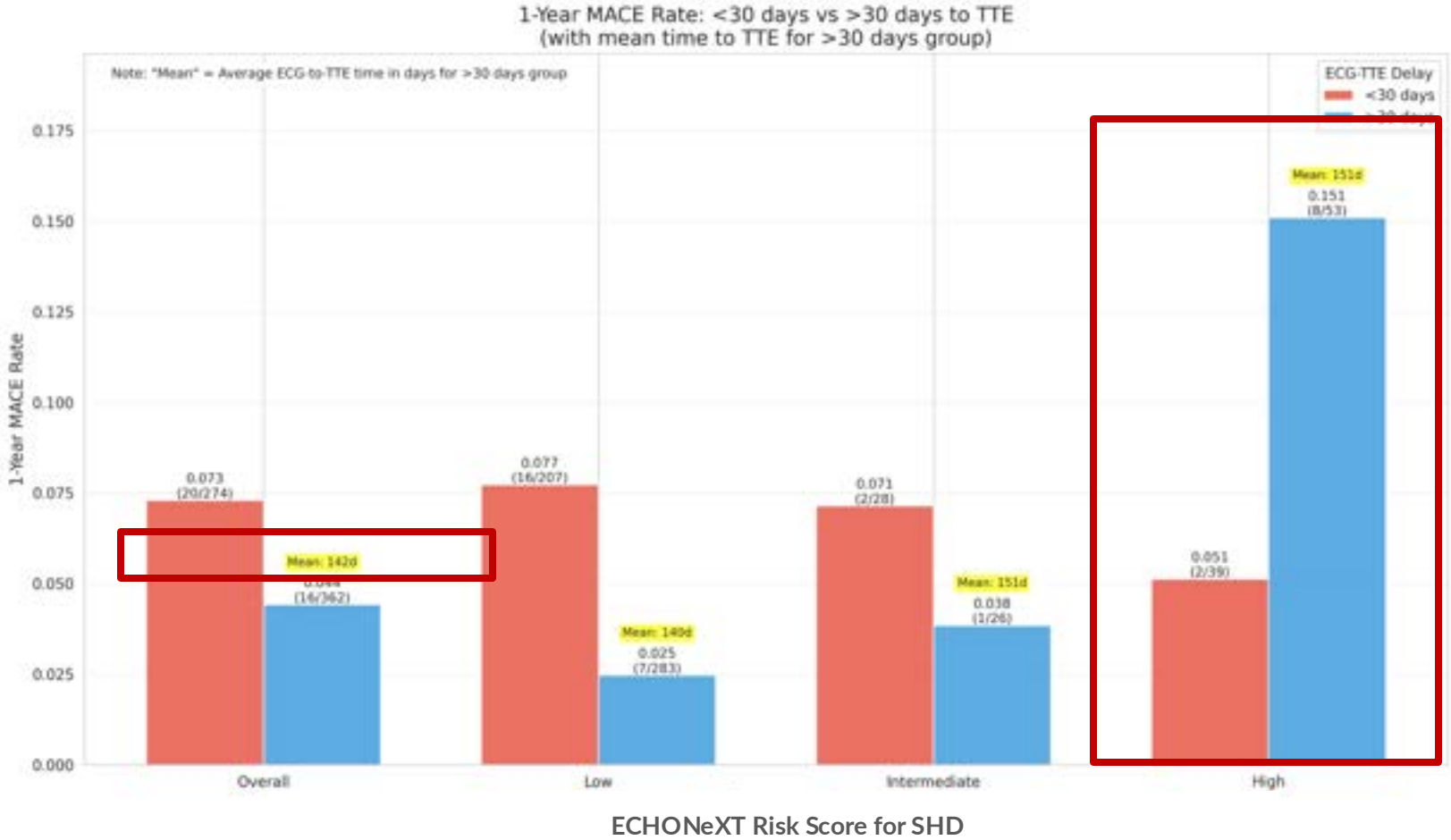
Diagnosis Time Comparison (Anticipated)



Key Findings

188% increase in SHD detection with AI (241 to 453 cases per 12 months)

86% reduction in diagnosis time for high-risk patients (210 to 30 days)

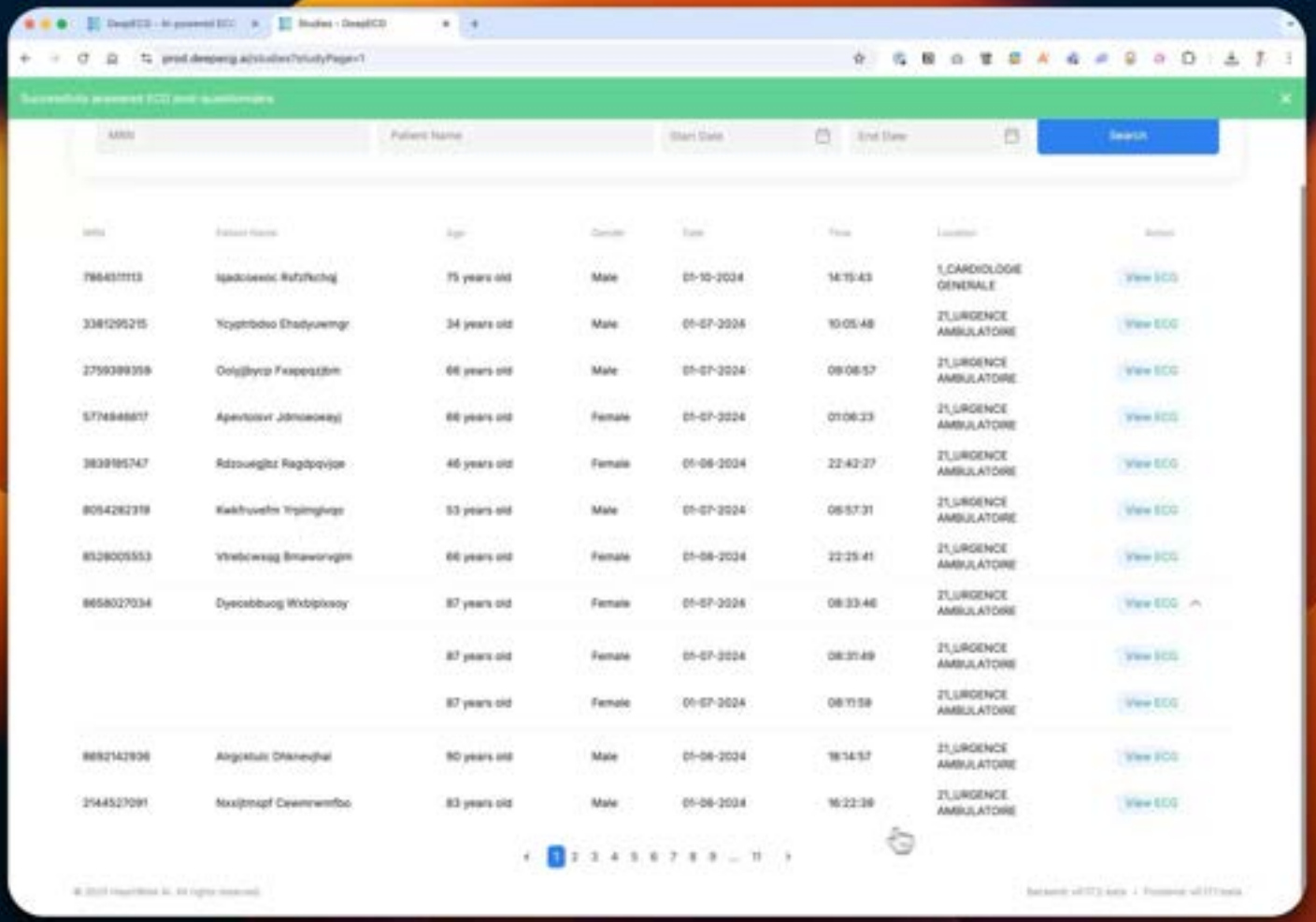


ECHONeXT Risk Score for SHD

15.1% vs 5.1% MACE (complications) at 1-year if trans-thoracic echocardiogram (TTE) performed ≥ 30 days in patients at high risk of SHD

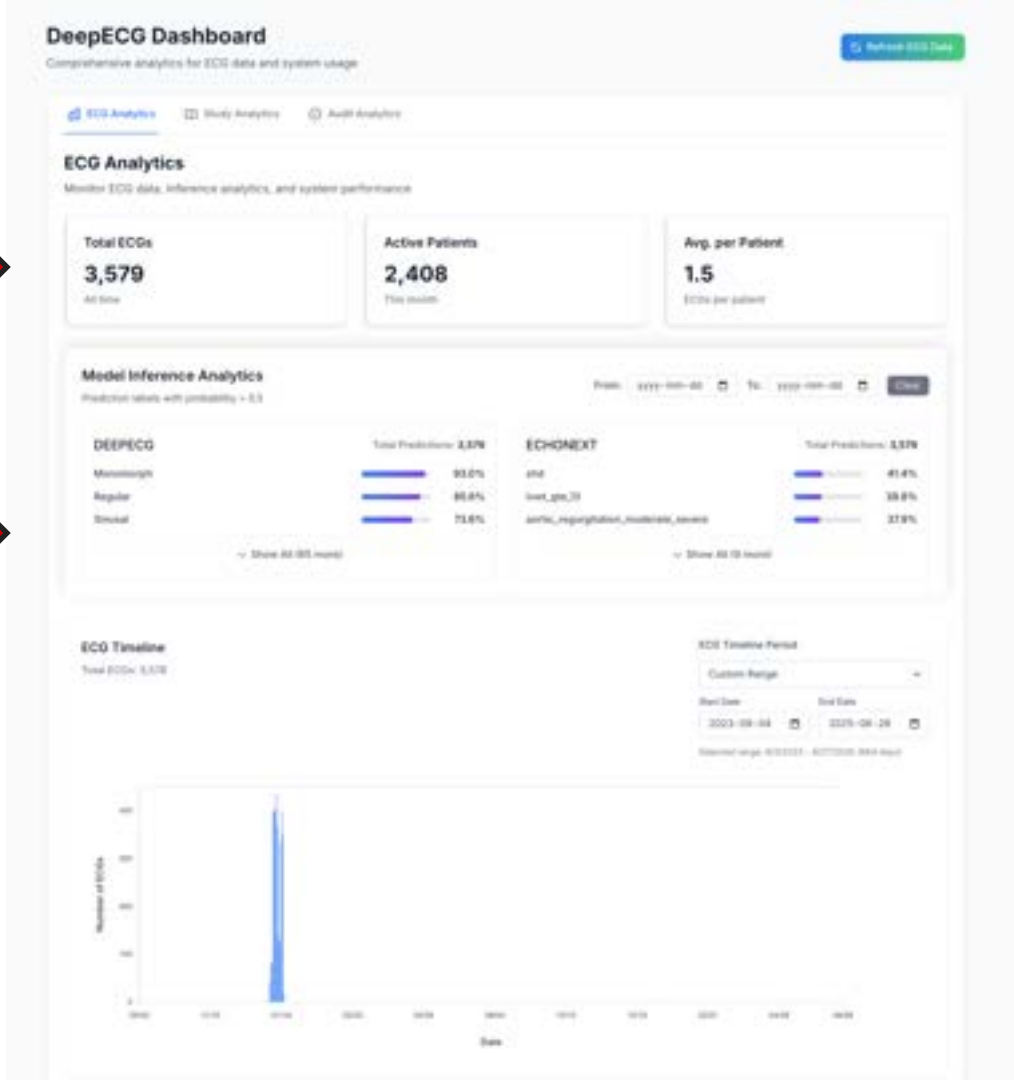
Average time between first ECG (First visit) and TTE = 141 days

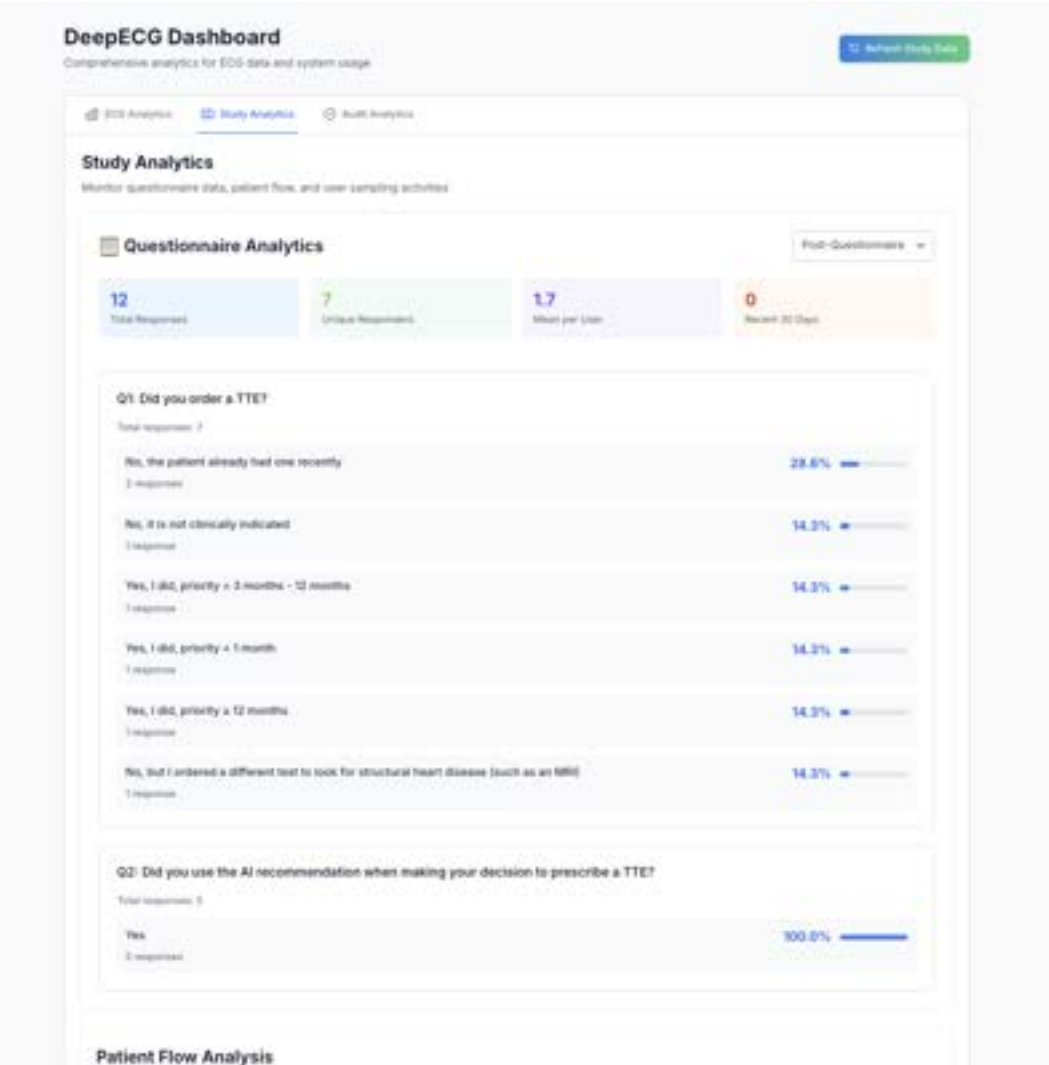
Dee


Search
Patient Name
Start Date
End Date
75 years old
Male
01-10-2024
14:15:43
1_CARDIOLOGIE GENERALE
34 years old
01-07-2024
10:05:48
21_URGENCE AMBULATOIRE
66 years old
09:08:57
46 years old
Female
01-06-2024
22:42:27
53 years old
08:57:31
87 years old
08:33:46
08:31:49
08:11:59
90 years old
18:14:57
83 years old
16:22:39

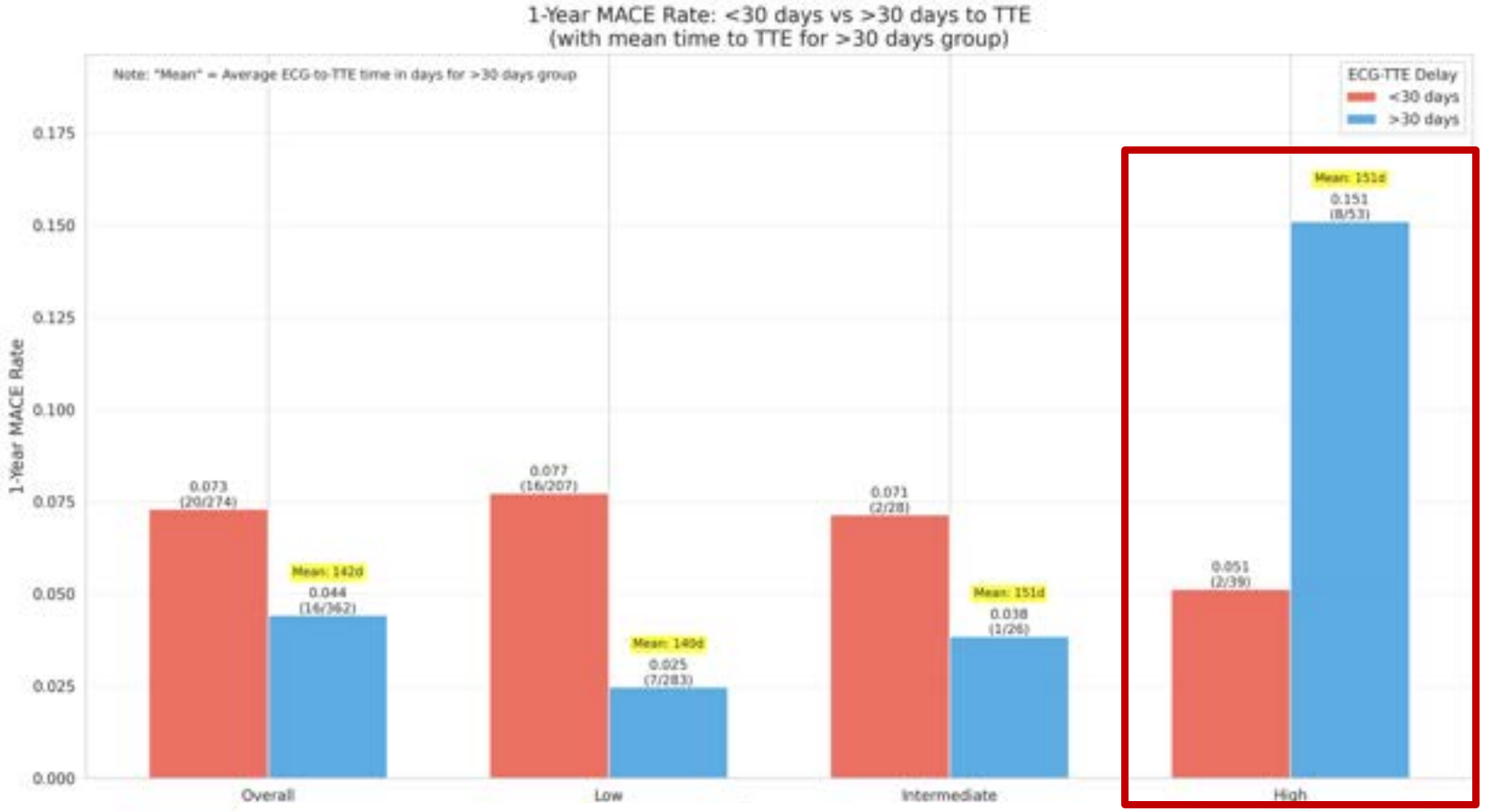
Total patients in the study

Most frequent predictions




DeepECG Dashboard
Comprehensive analytics for ECG data and system usage
Study Analytics
Monitor questionnaire data, patient flow, and user sampling activities
Questionnaire Analytics
12
7
1.7
0
Q1: Did you order a TTE?
No, the patient already had one recently
28.6%
No, it is not clinically indicated
14.3%
Yes, I did, priority = 3 months - 12 months
14.3%
Yes, I did, priority = 1 month
14.3%
Yes, I did, priority = 12 months
14.3%
No, but I ordered a different test to look for structural heart disease (such as an MRI)
14.3%
Q2: Did you use the AI recommendation when making your decision to prescribe a TTE?
Yes
100.0%
Patient Flow Analysis

Economic Analysis



ECHONeXT Risk Score for SHD

Incremental Cost-Effectiveness Ratio (ICER) Detailed Analysis with Platform Overhead

Key Assumptions

Screened patients:	10,000
AI-ECG fee:	$5.00 per test
Platform overhead:	$0.10 per ECG
Total cost per test:	**$5.10**
High-risk ECGs:	400
Baseline early detection:	200
AI early detection:	400
MACE rate (late detection):	15%
MACE rate (early detection):	5%
Hospital cost per MACE:	$10,000

ICER Calculation Results

Screening + platform cost:	$51,000
MACE events (usual care) @ 1 year:	24
MACE events (AI screen) @ 1 year:	16
Events avoided:	**8**
Hospital costs avoided:	$80,000
Net cost:	-$29,000

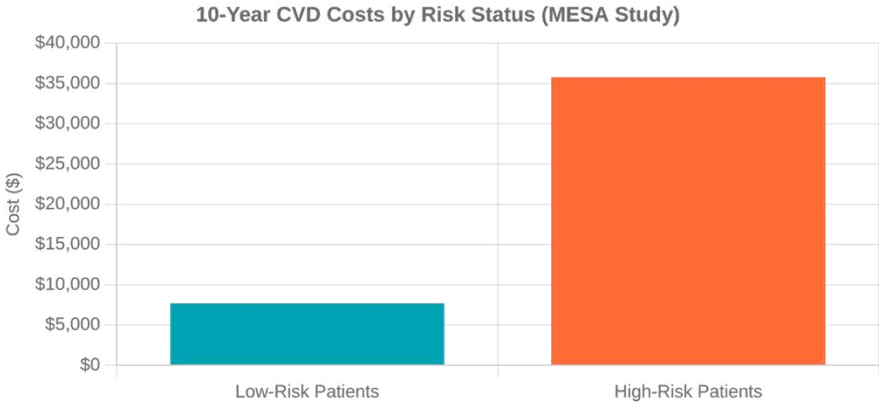
-$3,625

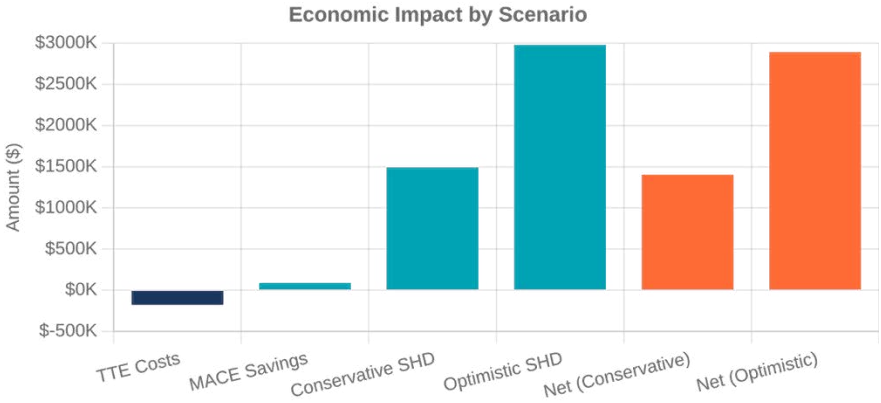
ICER (cost per MACE avoided)

Platform Overhead Impact

Platform overhead of $10,000 per100,000 ECGs translates to only $0.10 per ECG, adding minimal cost while enabling comprehensive monitoring and audit capabilities.

10-Year Cost Comparison: Low vs High Risk Patients





MESA Study 10-Year SHD Costs

- **Low-risk patients:** $7,700 (similar to treated SHD patients)
- **High-risk patients:** $35,800 (similar to high risk SHD patients)
- **Average difference:** $28,100 per patient over 10 years
- **Annual difference:** $2,810 per patient per year

Economic Value

- **Conservative scenario:** $1.4M net savings over 10 years
- **Optimistic scenario:** $2.9M net savings over 10 years
- **ROI (Conservative):** $7.95 saved per $1 invested
- **ROI (Optimistic):** $16.90 saved per $1 invested

Energy Effectiveness

Energy Consumption Assessment: DeepECG-SL vs DeepECG-SSL

DeepECG-SL

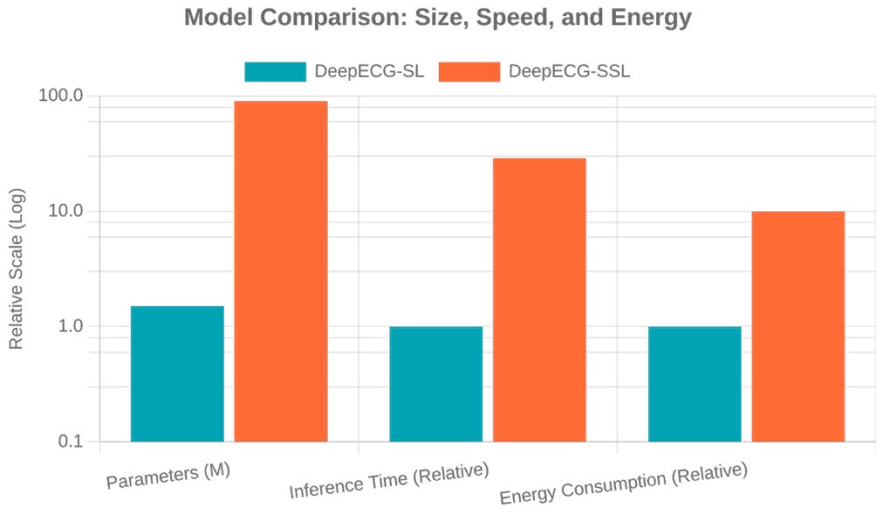
1.51M parameters
Optimized for efficiency
Lower energy consumption

DeepECG-SSL

90.37M parameters
Superior performance on rare classes
Enhanced fairness

Key Differences

DeepECG-SSL is **60x larger** than DeepECG-SL
Inference time is **29x longer** for SSL model
Energy consumption is **10x more intensive** (on CPU)
Trade-off between efficiency and performance



Performance vs Efficiency Trade-off

DeepECG-SL: Ideal for resource-constrained environments
DeepECG-SSL: Better for applications requiring high accuracy on rare conditions

Both models maintain clinical-grade performance
Choice depends on specific deployment requirements

Energy Assessment Methodology & Tools

Data Sources

EPA: Greenhouse gas emissions data

GlobalPetrolPrices.com: Worldwide electricity cost aggregator

CodeCarbon: Regional CO_2 emission factors

CO_2 to Distance Conversion

EPA standard: **400 gCO_2/mile**

Metric equivalent: **248.5 gCO_2/km**

Used for average passenger vehicle emissions

Provides tangible comparison for environmental impact

Assessment Scope

Included: Direct model inference energy consumption

Excluded: Hardware manufacturing costs

Excluded: Data transfer and storage energy

Excluded: Infrastructure maintenance energy

CodeCarbon

Primary tool for assessing energy usage and CO_2 production from kWh consumption worldwide. Provides accurate energy consumption measurements for model inference.

Global Scale & Context of ECG Testing

300M+

Global ECG tests annually

100M

US ECG tests annually

100K

Montreal Heart Institute annually

3

Case study scenarios

Case Study Scenarios

1 Million ECGs

Regional hospital network scale analysis

10 Million ECGs

Large healthcare system or national program

100 Million ECGs

Country-wide or multi-national deployment

Regional Energy Analysis Results

CA

Quebec, Canada

$0.12 CAD/kWh

Lowest electricity costs due to abundant hydroelectric power. Most cost-effective region for AI deployment.

US

USA (Average)

$0.17 CAD/kWh

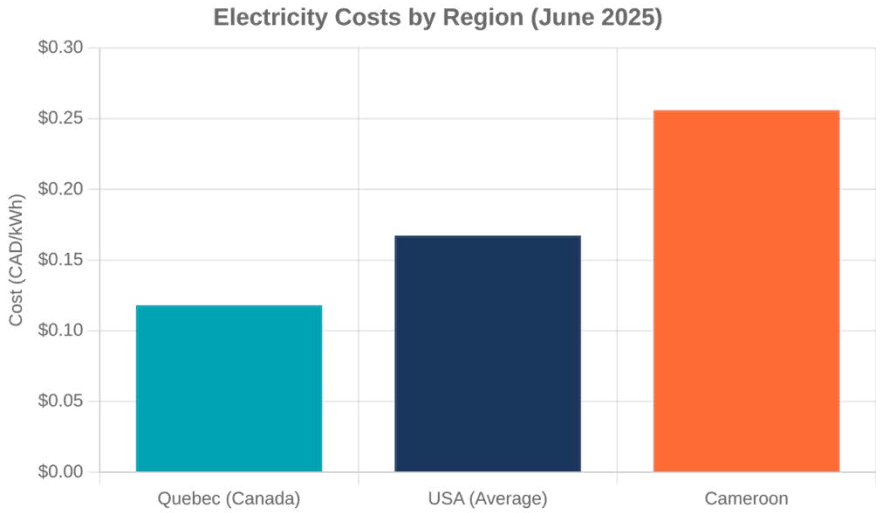
Moderate electricity costs representing the national average across diverse energy sources.

CM

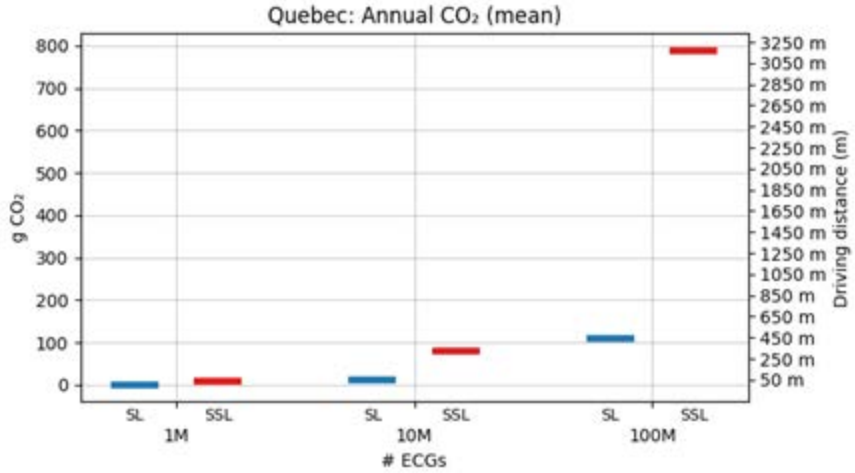
Cameroon

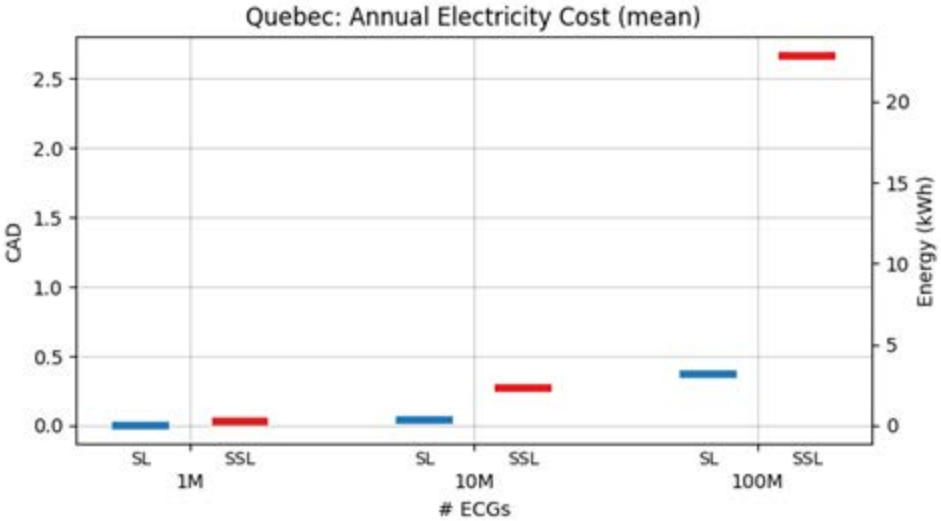
$0.26 CAD/kWh

Highest electricity costs among studied regions, representing developing economy energy pricing.

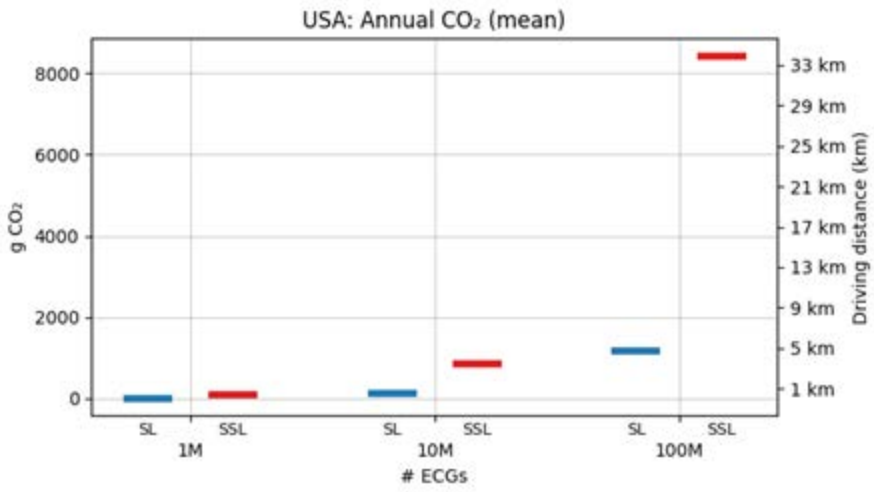


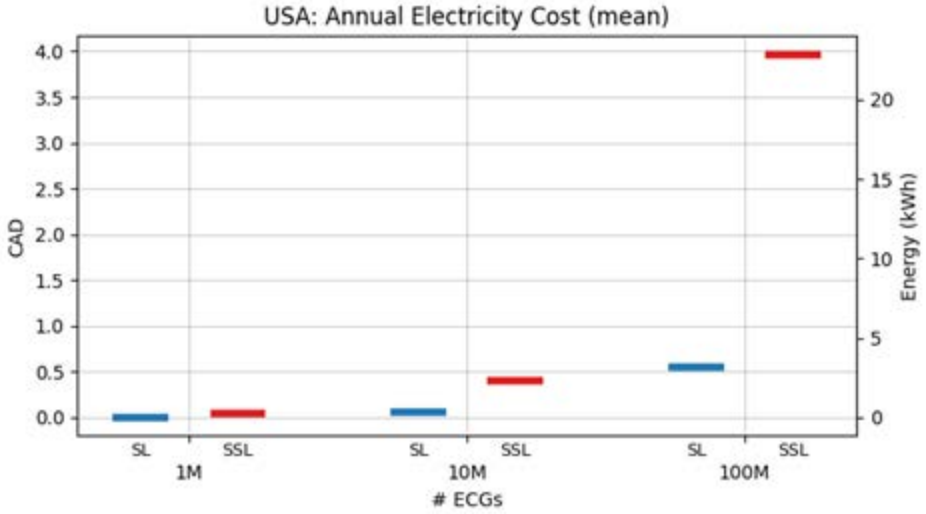
Québec


Quebec: Annual CO_2 (mean)
g CO_2
Driving distance (m)
SL
SSL
1M
10M
100M
ECGs

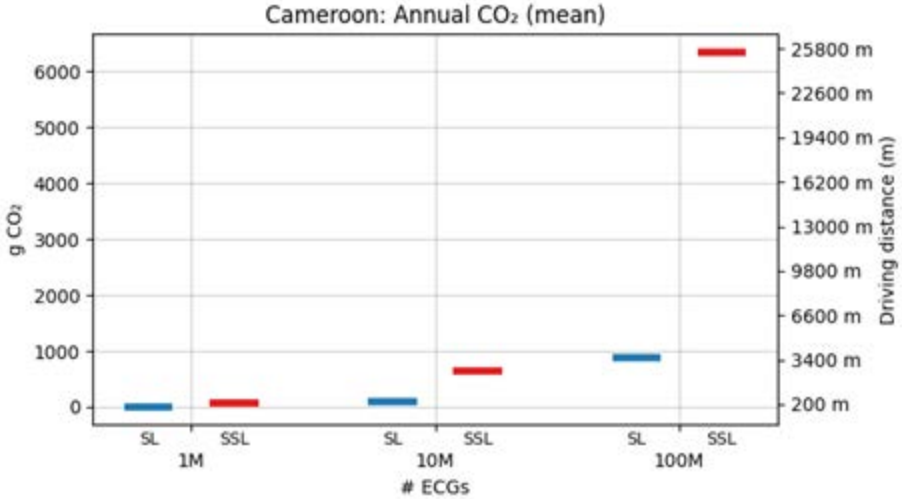

Quebec: Annual Electricity Cost (mean)
CAD
Energy (kWh)
SL
SSL
1M
10M
100M
ECGs

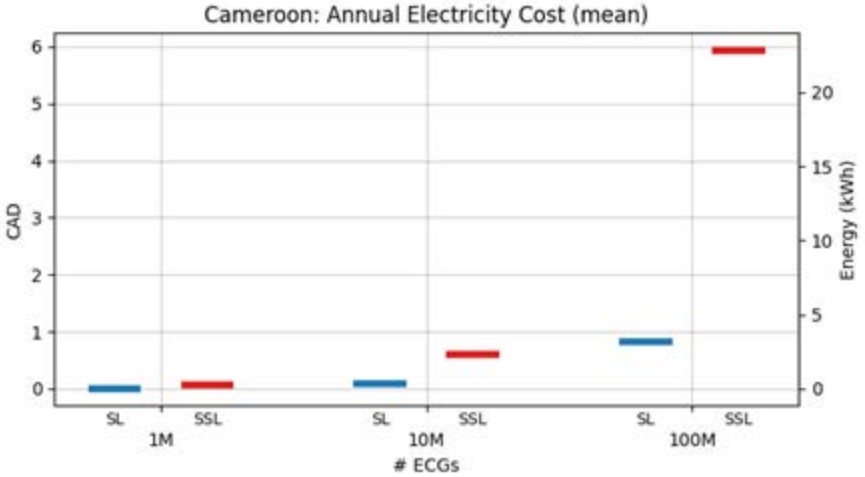
USA


USA: Annual CO_2 (mean)
g CO_2
8000
6000
4000
2000
0
33 km
29 km
25 km
21 km
17 km
13 km
9 km
5 km
1 km
Driving distance (km)
SL
SSL
1M
10M
100M
ECGs


USA: Annual Electricity Cost (mean)
CAD
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
20
15
10
5
0
Energy (kWh)
SL
SSL
1M
10M
100M
ECGs

Cameroon


Cameroon: Annual CO_2 (mean)
g CO_2
Driving distance (m)
6000
5000
4000
3000
2000
1000
0
25800 m
22600 m
19400 m
16200 m
13000 m
9800 m
6600 m
3400 m
200 m
SL
SSL
1M
10M
100M
ECGs


Cameroon: Annual Electricity Cost (mean)
CAD
Energy (kWh)
6
5
4
3
2
1
0
20
15
10
5
0
SL
SSL
1M
10M
100M
ECGs

Environmental Impact: Putting Energy Consumption in Perspective

Scale Comparisons

- **Daily commute:** Average person drives ~40km/day
- **Short flight:** Montreal to Toronto (~500km) = 14x more emissions
- **Home energy:** Average household uses ~30 kWh/day
- **Healthcare impact:** 100M ECG analyses could save thousands of lives

Environmental Context

EPA standard: **248.5 gCO_2/km** for average car

100M ECG analyses = **35km of driving**

Minimal environmental impact at massive scale

Sustainable AI deployment for healthcare

35 km

Maximum car travel equivalent

100M ECG analyses with DeepECG-SSL

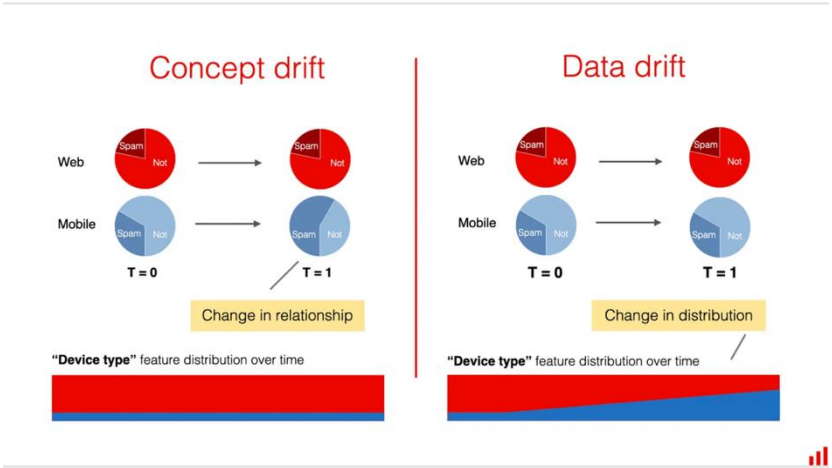
$6 CAD

Maximum electricity cost

100M ECG analyses with DeepECG-SSL

Lifelong Learning

The Challenge: Model Drift in Healthcare AI



Current Limitations

Static AI models in healthcare suffer from performance degradation over time, particularly crucial in cardiology where diagnostic criteria evolve

Why Current AI Models Degrade

Concept drift: Relationship between input data and target variable changes over time

Evolving medical knowledge: Diagnostic criteria and treatment guidelines change

The Gap

No study has successfully implemented a continuous learning framework for ECG interpretation in a clinical setting

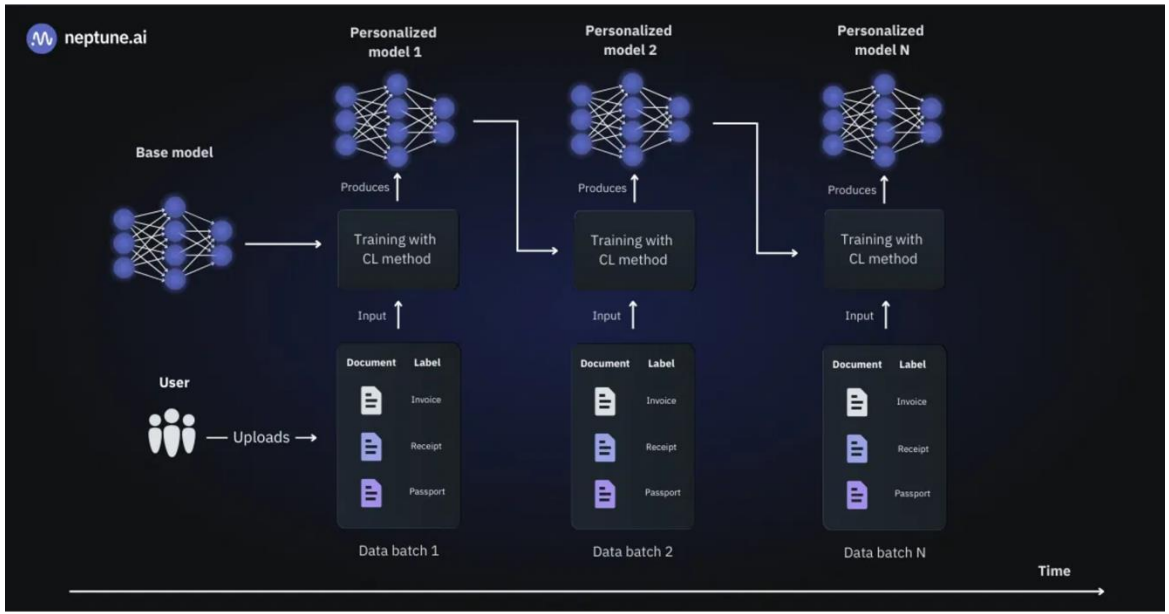
Continual Learning Framework for DeepECG.ai

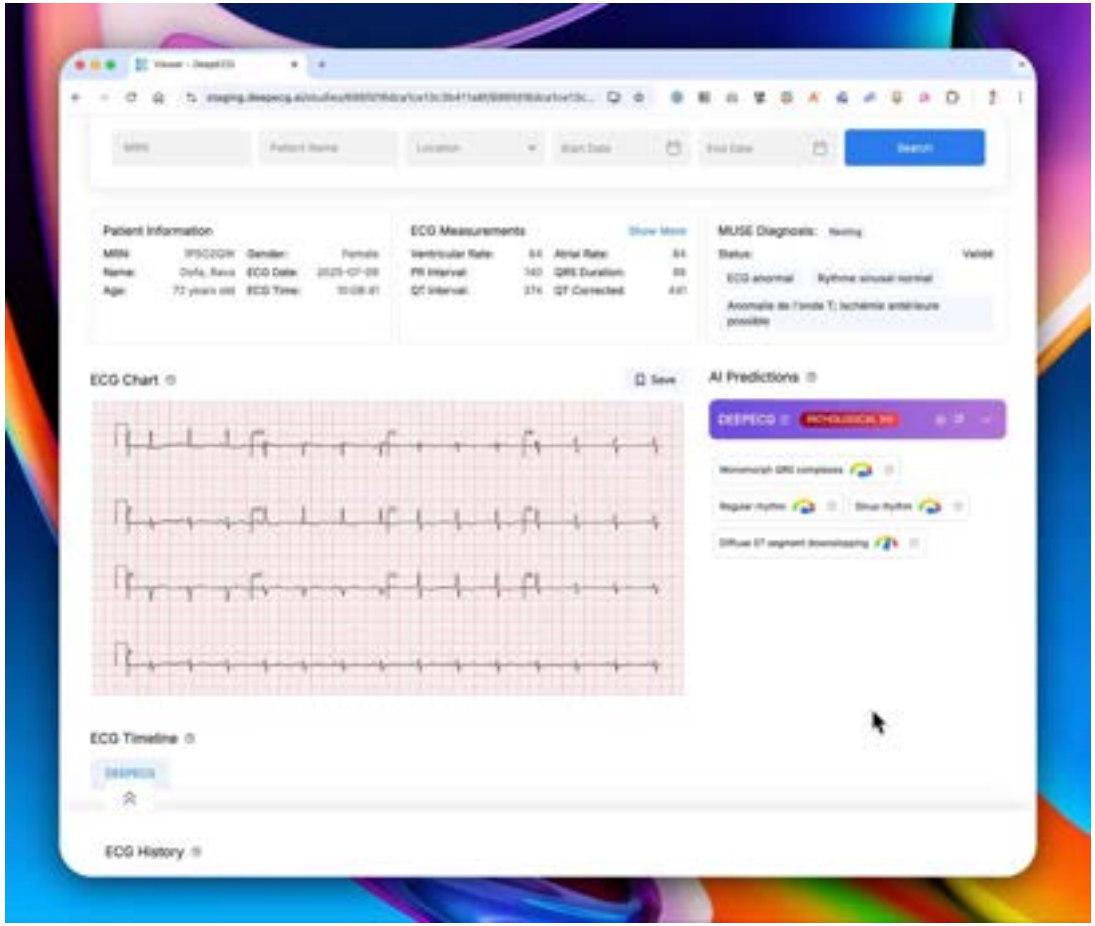
Key Framework Components

Selective model updates : Targeted improvements without disrupting stable areas

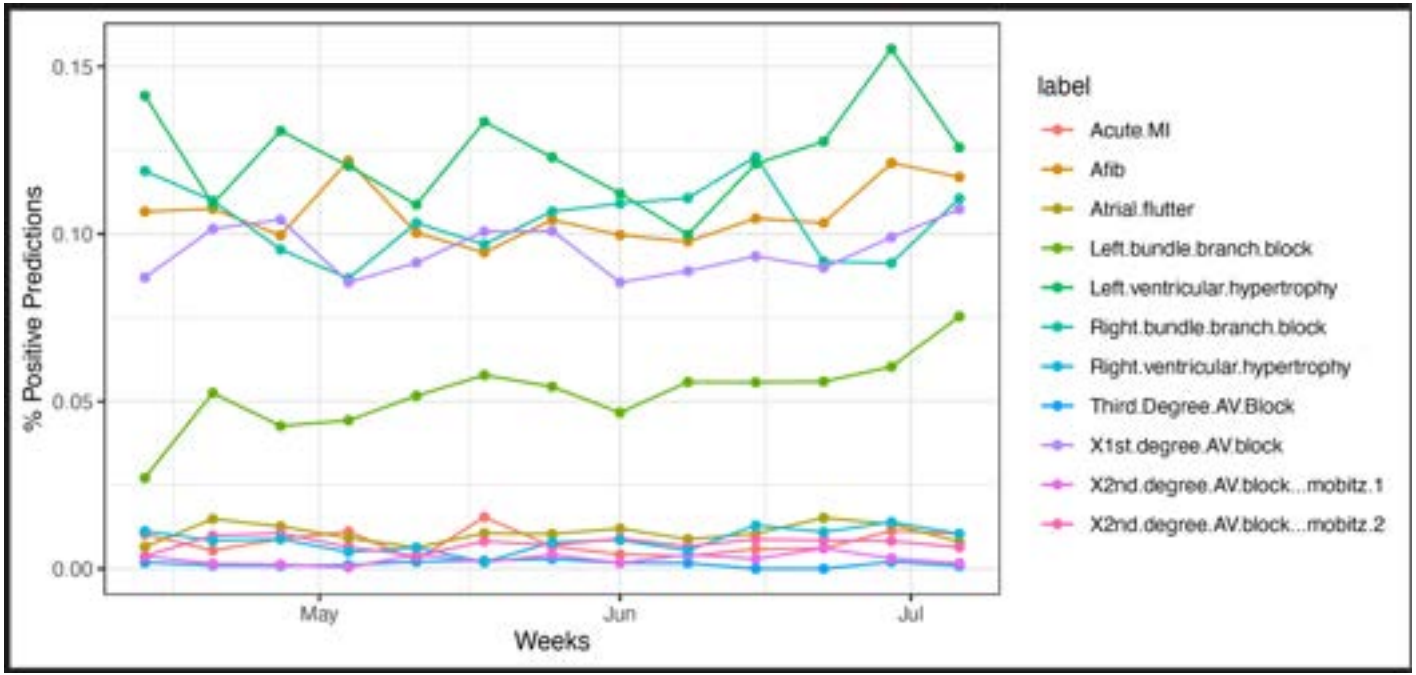
Knowledge retention : Preserving previously learned patterns

Catastrophic forgetting prevention: Maintaining performance on existing tasks




Search
Patient Information
ECG Measurements
Show More
MUSE Diagnosis:
Status:
Valide
ECG Chart
Save
AI Predictions
ECG Timeline
ECG History

Implementation & Safeguards

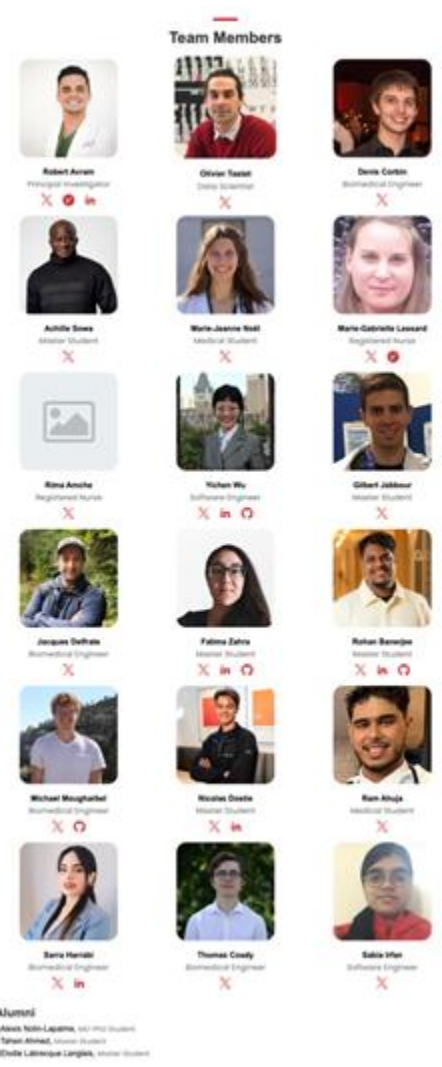


Performance Monitoring

Real-time dashboard tracking model performance by diagnostic class
Model kept static during the study but multiple models in “SHADOW mode”
Automated alerts if performance degrades >10% over 3 continuous days

DeepECG in a Nutshell

- **Open-source** foundation models (DeepECG-SL, DeepECG-SSL) with **expert-level ECG AI** (AUROC >0.98) across **10+ datasets**
- **SHD detection ↑188 % SHD diagnosis ↓86%** decrease in time to diagnosis (HEART-AI Pilot trial)
- **Cost-effective**: ICER = **$1,375/MACE (6-10 less MACE per year) avoided; $1.4M-2.9M at 10 years in SHD related costs for disease progression avoided.**
- **Green AI**: 100M ECGs analysed = **35 km car drive – 20 kWH – 6$ at worse**
- **Scalable, Docker-ready, clinically validated**



Thank You

Do you have any questions?

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Robert Avram

Scan to connect

HeartWise.AI

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Online Resources:

www.pacsai.co | www.deepecg.ai | https://github.com/HeartWise-AI/DeepECG_Docker