

# Multimodal Artificial Intelligence for Cardiac Amyloidosis Diagnosis:

Integrating Echocardiography with Clinical and Laboratory Data for Improved Detection

**Jeremy Slivnick, MD, FACC, FASE**

Assistant Professor

The University of Chicago Medicine

Division of Cardiovascular Medicine

Twitter: @JSlivnickMD



AT THE FOREFRONT

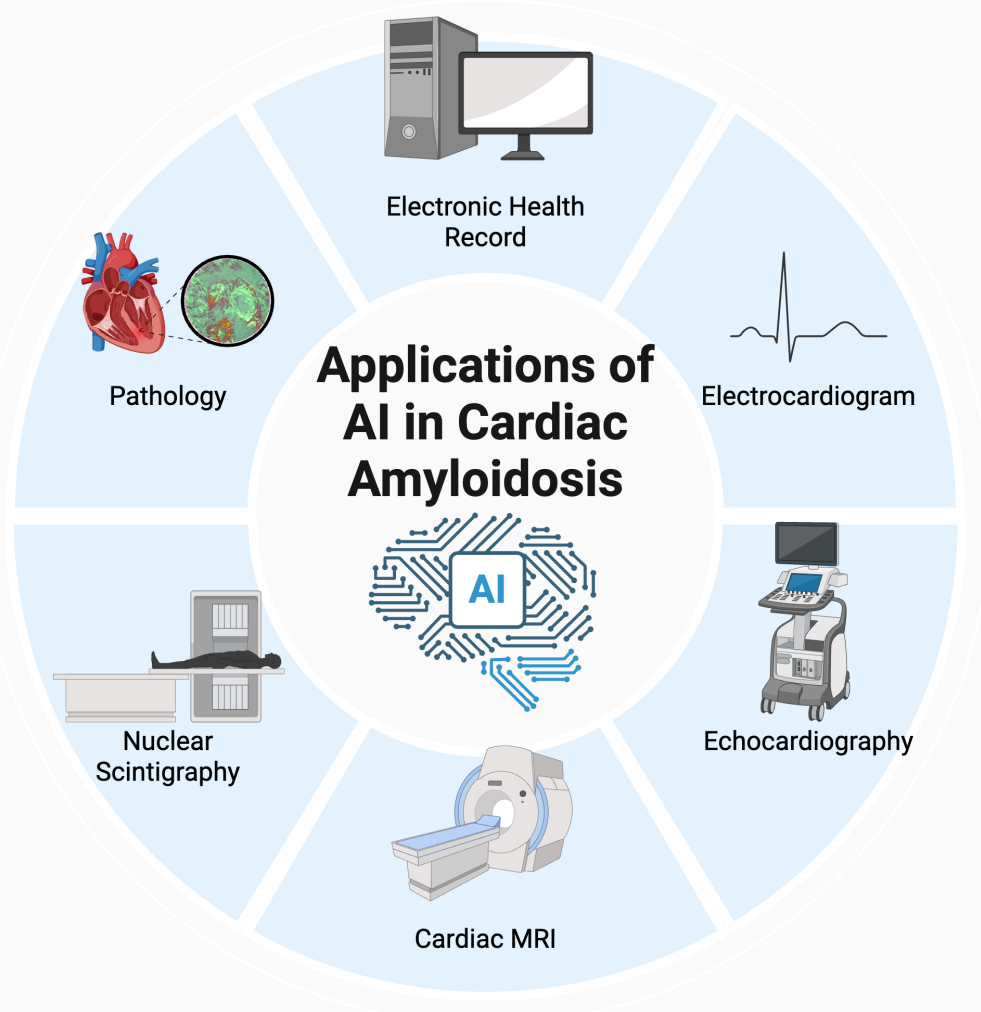
**UChicago Medicine**

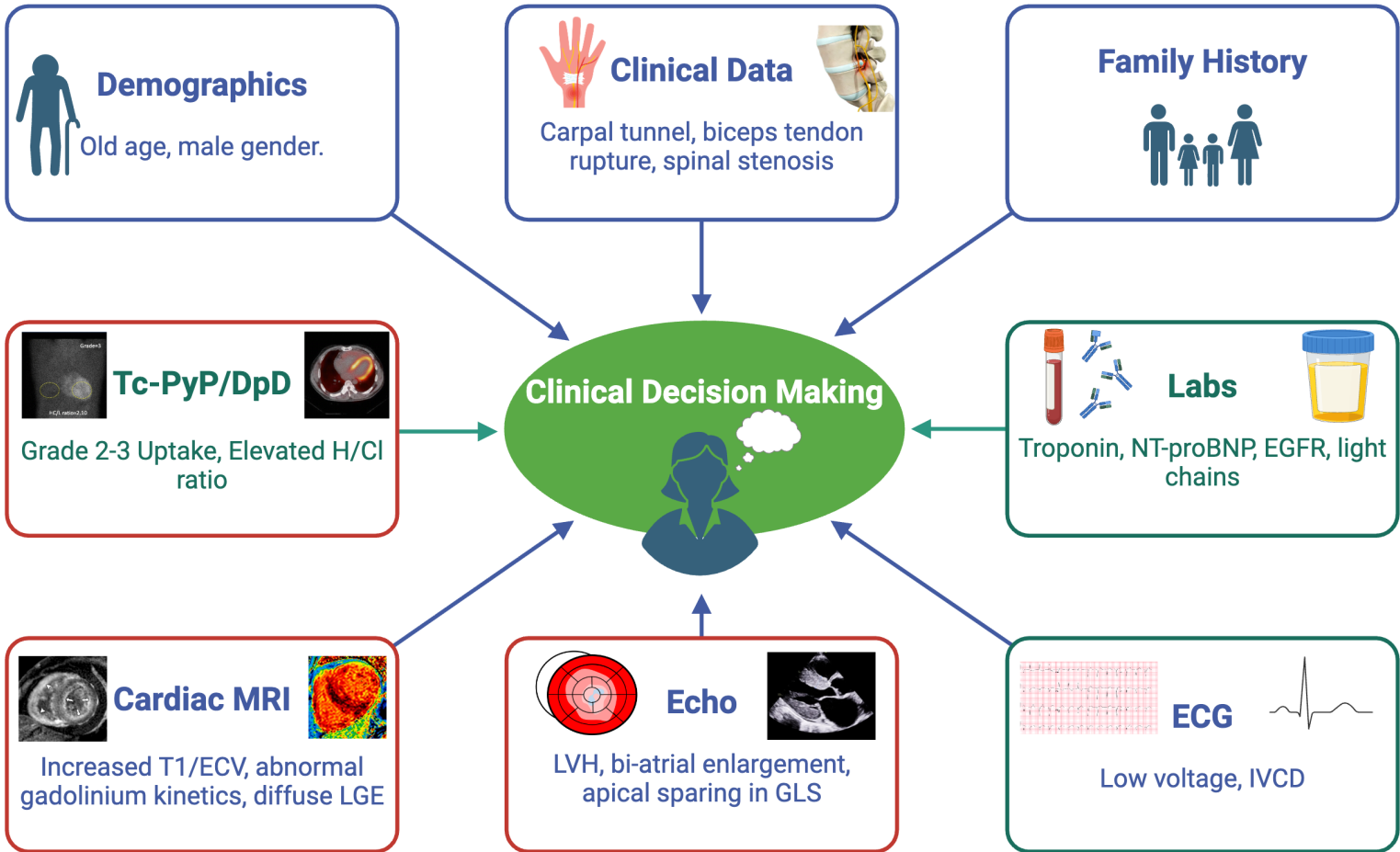
# Disclosures

- Advisory boards: Alnylam, BridgeBio, Pfizer
- Consulting: GE Healthcare
- Study received with in kind support from Us2.AI

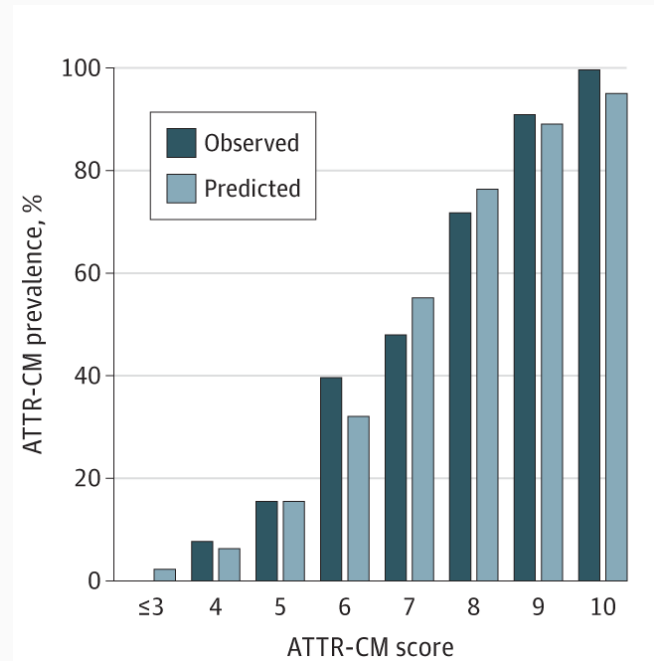
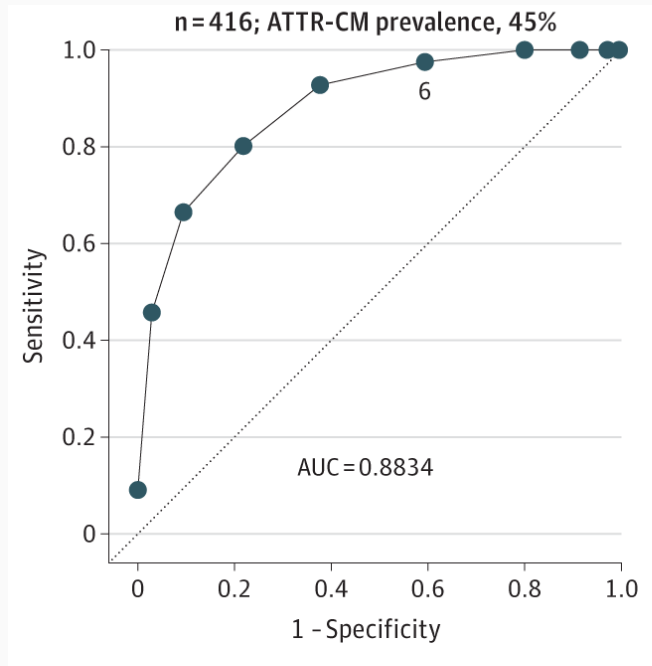
# Background

- AI algorithms have shown potential to improve cardiac amyloid detection.
- Ioannou, Fontana *et al* previously developed a deep learning pattern recognition model for CA detection from a single apical 4-chamber view (**AI-PRM**).
- Yet, a limitation of these models has been reliance on single modalities.





# Background



**Input Features:** Age, Male sex, hypertension, relative wall thickness, increased wall thickness, and LVEF

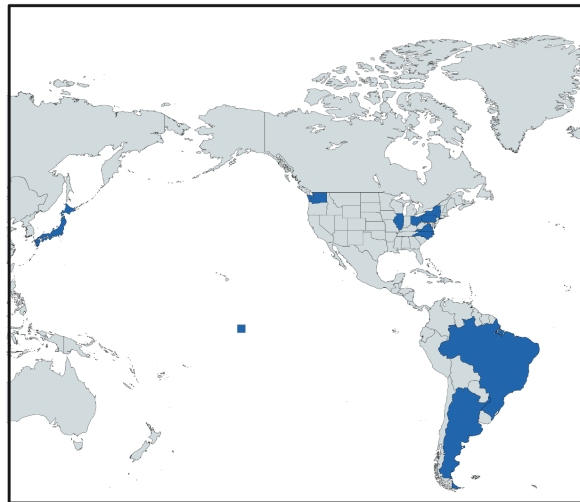
# Hypothesis

- We hypothesized that a model (**AI-ECM**) integrating clinical, lab, and echo parameters into the AI echo model would similarly augment performance compared to **AI-PRM** alone

# Methods

- Amyloidosis International Imaging Collaborative Study.
- 1,031 Patients
  - 720 Cardiac Amyloidosis
  - 311 Phenotypic Controls

Multicenter, International Cohort (AICC)  
(9 Sites)



Cardiac Amyloid (n=720)

Phenotypic Controls (n=311)

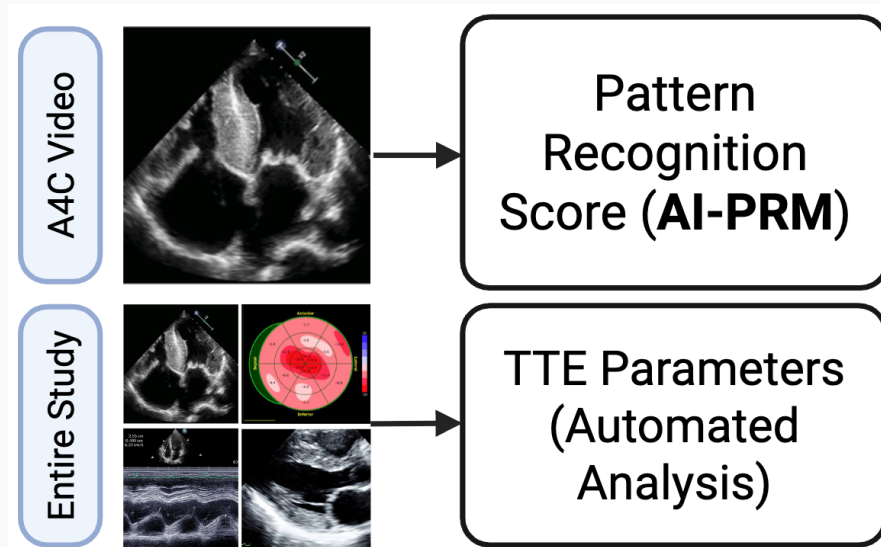
ATTR-CA (n=388)  
AL-CA (n=312)  
Unknown (n=20)

PyP Neg Controls  
(n=197)  
Systemic AL w/o CA  
(n=114)



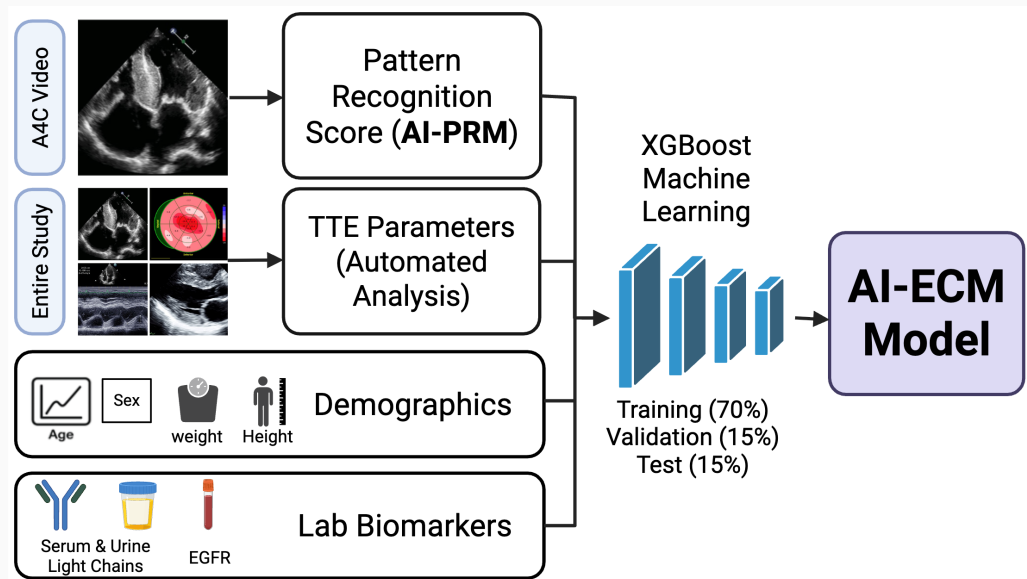
# Methods

- A4C automatically detected and analyzed by deep learning model (**AI-PRM**).
- Echocardiographic Parameters automatically quantified using commercially available AI platform (Us2.AI):
  - Septal apical-to-basal ratio (SAB)
  - Relative Wall Thickness (RWT)
  - RV S'
  - Doppler E/e' Ratio
  - TAPSE

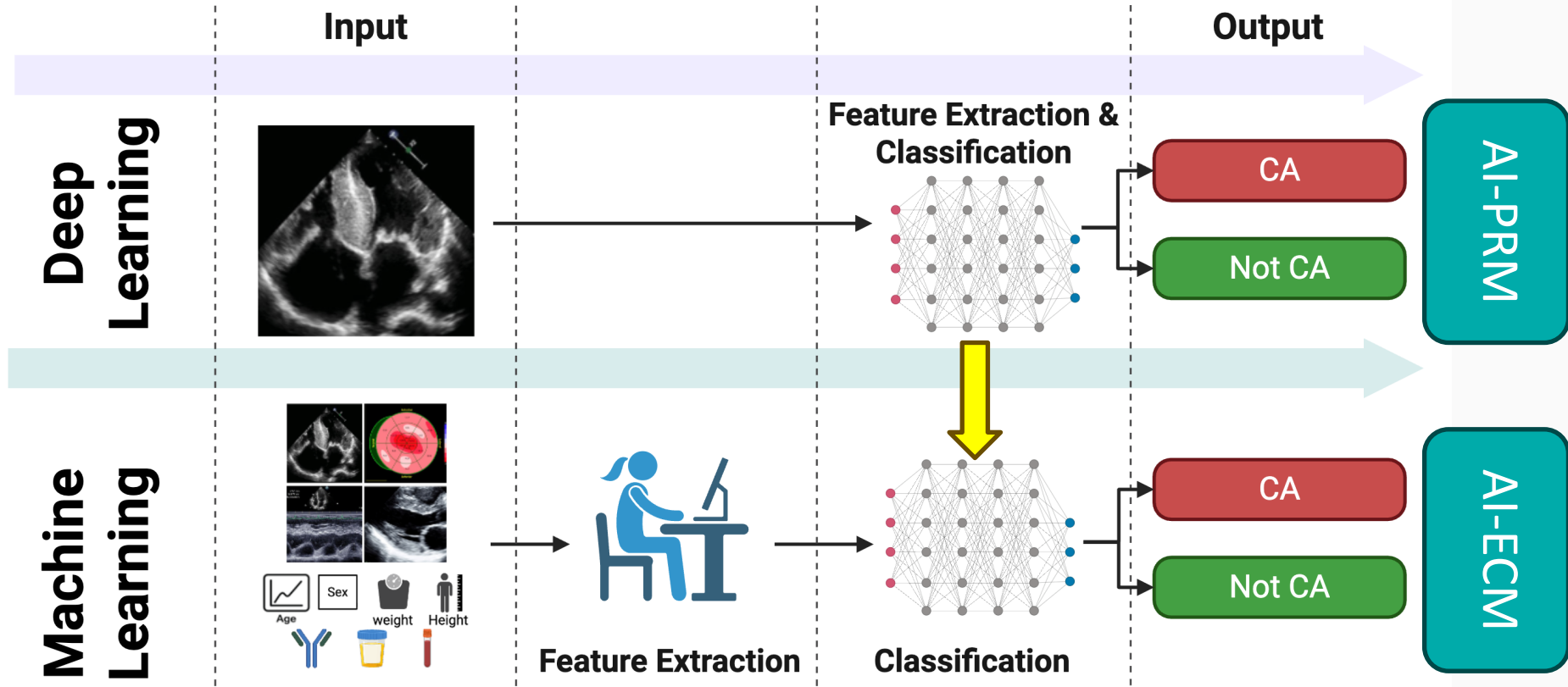


# Methods

- Dataset split into training, validation, and test (70%/15%/15%) datasets.
- AI Combined Echo Clinical Model (**AI-ECM**) trained using XGBoost model\* in step-wise manner.
- Hyperparameters optimized via 5-fold cross-validation in training and validation datasets



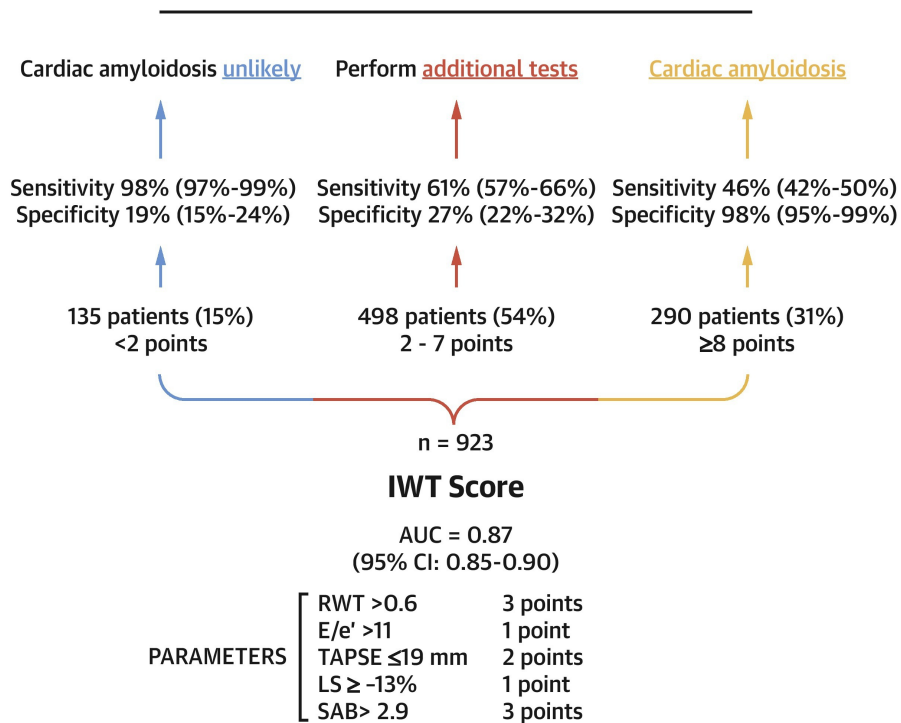
**Input Features: AI-PRM, RWT, SAB, age, gender, height, weight, BMI, EGFR, light chain biomarkers**



# Methods

- Model accuracy evaluated using AUC, sensitivity, specificity, and accuracy.
- AUC of **AI-ECM** compared to **AI-PRM** and conventional **IWT** score using DeLong method.
- Sub-analysis comparing AI-ECM to IWT and AL score performed in relevant subpopulations.

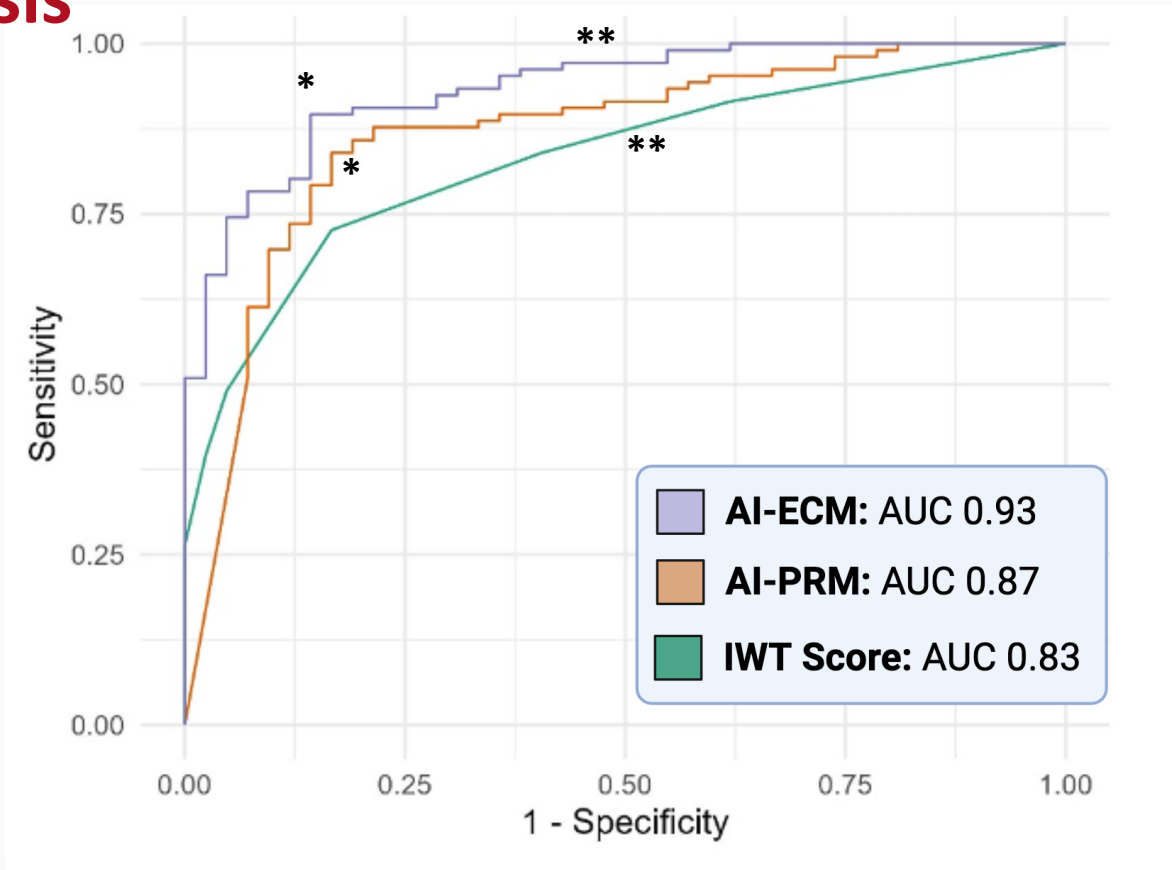
## IWT Score



# Study Population

Clinical characteristic	CA Cases (N=720)	Controls (N=311)
Age, years, mean $\pm$ SD	70.9 $\pm$ 11.0	69.3 $\pm$ 13.8
Weight, kg, mean $\pm$ SD	78.4 $\pm$ 19.8	82.5 $\pm$ 22.0
Height, cm, mean $\pm$ SD	170.7 $\pm$ 11.6	169.1 $\pm$ 11.4
BMI, kg/m <sup>2</sup> , mean $\pm$ SD	26.8 $\pm$ 6.1	28.9 $\pm$ 7.6
Gender, male, n (%)	531 (73.8%)	179 (57.6%)
Ethnicity, n (%)		
- Black	211 (29.3%)	102 (32.8%)
- Hispanic or Latino	118 (16.4%)	19 (6.1%)
- White	279 (38.8%)	162 (52.1%)
- Others/ Not reported	112 (15.6%)	28 (9.0%)
NT-proBNP, pg/ml, median (IQR)	2492.0 (710.5-6542.3)	812.7 (182.0-3804.0)
BNP, pg/ml, median (IQR)	514.0 (240.0-931.0)	87.0 (41.0-280.9)
Creatinine, mg/dL, median (IQR)	1.22 (0.95-1.69)	1.14 (0.88-1.82)
eGFR, mL/min/1.73m <sup>2</sup> , median (IQR)	56.3 (36.9-72.0)	59.0 (34.0-80.0)
RWT, mean $\pm$ SD	0.7 $\pm$ 0.2	0.5 $\pm$ 0.1
TAPSE, mm, mean $\pm$ SD	17.8 $\pm$ 4.9	21.8 $\pm$ 5.2
E/e' Mean, mean $\pm$ SD	17.0 $\pm$ 6.5	12.6 $\pm$ 6.0
A4C LV GLS, %, mean $\pm$ SD	-13.9 $\pm$ 5.1	-16.2 $\pm$ 5.1
A4C LV SAB, mean $\pm$ SD	2.2 $\pm$ 1.1	1.5 $\pm$ 0.7
LV SAB, mean $\pm$ SD	2.2 $\pm$ 1.0	1.4 $\pm$ 0.5

# ROC Analysis



\*:  $p=0.007$  (AI-ECM vs AI-PRM)

\*\* :  $p=0.004$  (AI-ECM vs IWT Score)

# Feature Importance

Feature	Feature Importance
AI-PRM	10.99
RWT	3.35
Abnormal Urine Monoclonal Protein Present (Immunofixation)	2.13
Gender	2.00
Abnormal Serum Monoclonal Protein Present (Immunofixation)	1.83
EGFR	1.44
LV Apex-to-Basal Strain Ratio	1.41
Serum Kappa	1.28
Age	1.15
Serum Lambda	1.15
Weight	1.12
Height	1.06
BMI	1.02
Creatinine	0.94

# Model Comparison

Model	Accuracy (%)	Sensitivity (%) (95% CI)	Specificity (%) (95% CI)	AUC (95% CI)	Yield (%)
IWT Score	56%	40%	98%	0.83 (0.76 - 0.90)	100%
AI-PRM Score	81%	77%	90%	0.87 (0.80-0.94)	92%
AI-PRM+TTE Parameters	84%	83%	86%	0.89 (0.84 - 0.94)	100%
AI-PRM+TTE+Clin	82%	81%	86%	0.90 (0.85-0.95)	100%
AI-ECM	89%	90%	86%	0.94 (0.90 - 0.97)	100%

# Subgroup Analysis

## ATTR Subgroup

(ATTR-CA vs PyP-negative Controls)

	Accuracy (%)	Sens (%)	Spec (%)	AUC	Yield (%)
IWT Score	61%	46%	96%	0.84	100%
AI-PRM	84%	82%	88%	0.86	98%
AI-ECM	90%	91%	88%	0.94	100%

## AL Subgroup

(AL-CA vs AL controls without CA)

	Accuracy (%)	Sens (%)	Spec (%)	AUC	Yield (%)
AL Score	51%	34%	100%	0.86	100%
AI-PRM	76%	68%	93%	0.89	84%
AI-ECM	86%	87%	81%	0.91	100%

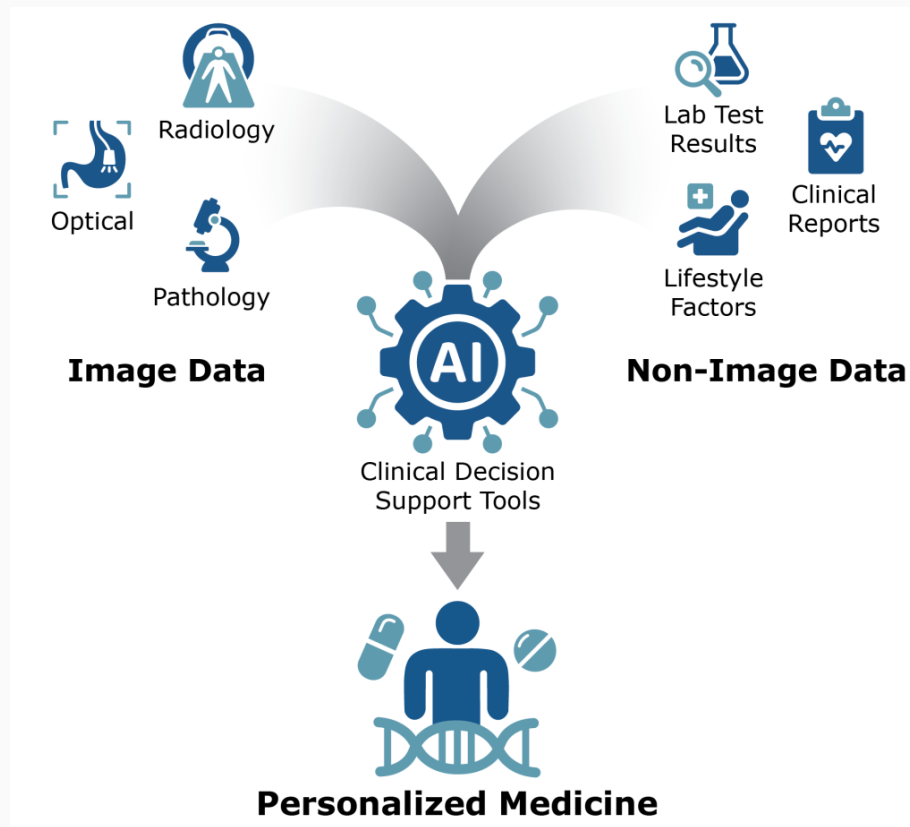
# Limitations

- External validation is needed.
- Prevalence does not mimic real world screening.
- Did not incorporate traditional red flag clinical parameters.
- Performance in early-stage disease is unknown.

# Conclusions

- The **AI-ECM** outperformed **AI-PRM** and **IWT** scores for CA detection in a large, multi-ethnic international dataset without the use of indeterminate classifications.
- Although more work is needed prior to deployment in clinical practice, the integration of clinical, lab, and echo biomarkers has the potential to augment AI-based echocardiographic detection of CA.

# Potential Future Implications



# Thank You

## AIRC Co-Investigators

Michael Randazzo, MD

Mathew Maurer, MD

Stephen Helmke

Marielle Scherrer-Crosbie, MD,  
PhD

Azin Vakilpour, MD

Karolina M. Zareba, MD

Akash Goyal, MD

Richard Cheng, MD

Nicole Wakamatsu, MD

Tetsuji Kitano, MD

Masaaki Takeuchi, MD

Viviane Tiemi Hotta, MD

Marcelo Luiz Campos Vieira, MD

Pablo Elissamburu, MD

Ricardo E. Ronderos, MD

Aldo Prado, MD

Efstratos Koutroumpakis, MD

Anita Deswal, MD

Amit Pursnani, MD

Nitasha Sarswat, MD

Karima Addetia, MD

Juan Cotella, MD

Frederick Ruberg, MD

Roberto Lang, MD

Federico Asch, MD

Federico Asch, MD

Roberto Lang, MD

## Mentors

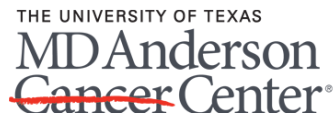
## Industry Collaborators

Sze Chi Lim

Matthew Frost

Carolyn Lam Su Ping, MD

Us2.Ai team





In Memorium to Roberto Lang

## Model From Clinical Perspective

Model	Accuracy (%)	Sensitivity (%) (95% CI)	Specificity (%) (95% CI)	AUC (95% CI)	Yield (%)
IWT Score	56%	40%	98%	0.83 (0.76 - 0.90)	100%
AI-PRM Score	81%	77%	90%	0.87 (0.80-0.94)	92%
Clin Only	47%	31%	86%	0.67 (0.57-0.77)	92%
Clin + Lab	71%	65%	86%	0.85 (0.77-0.92)	100%
Clin + Lab + TTE Parameters	81%	79%	86%	0.91 (0.86-0.95)	100%
<b>AI-ECM</b>	89%	90%	86%	0.93 (0.89-0.97)	100%

# Collinearity Between Parameters



# Thank You

## AIRC Co-Investigators

Michael Randazzo, MD

Mathew Maurer, MD

Stephen Helmke

Marielle Scherrer-Crosbie, MD,  
PhD

Azin Vakilpour, MD

Karolina M. Zareba, MD

Akash Goyal, MD

Richard Cheng, MD

Nicole Wakamatsu, MD

Tetsuji Kitano, MD

Masaaki Takeuchi, MD

Viviane Tiemi Hotta, MD

Marcelo Luiz Campos Vieira, MD

Pablo Elissamburu, MD

Ricardo E. Ronderos, MD

Aldo Prado, MD

Efstratos Koutroumpakis, MD

Anita Deswal, MD

Amit Pursnani, MD

Nitasha Sarswat, MD

Karima Addetia, MD

Juan Cotella, MD

Frederick Ruberg, MD

Roberto Lang, MD

Federico Asch, MD

Federico Asch, MD

Roberto Lang, MD

## Mentors

## Industry Collaborators

Sze Chi Lim

Matthew Frost

Carolyn Lam Su Ping, MD

Us2.Ai team

