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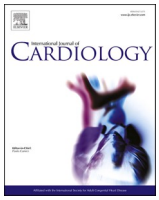

Clinical and artificial intelligence assessed echocardiographic predictors of outcomes after acute myocardial infarction

Chris Lenselink [a,b], Yee How Lau [a], Weiting Huang [a,c], See Hooi Ewe [a,c], Siau Chien Chiong [a], Choon Ta Ng [a,c], Kim Ricken [b], Erik Lipsic [b], Adriaan Voors [b], Carolyn Su Ping Lam [a,c], Khung Keong Yeo [a,c], Jonathan Yap [a,c,*]

[a] Department of Cardiology, National Heart Centre Singapore, Singapore
[b] Department of Cardiology, University Medical Center Groningen, University of Groningen, Groningen, the Netherlands
[c] Duke-NUS Medical School, Singapore

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ABSTRACT

Background: Early risk stratification in patients after acute myocardial infarction (AMI) is critical for guiding therapy and resource allocation. While left ventricular ejection fraction (LVEF) is routinely assessed by echocardiography, novel markers offer additional prognostic utility but are not widely assessed due to time constraints or limited expertise. Artificial intelligence (AI) enables rapid, fully automated analysis of echocardiograms, producing standardized, comprehensive measurements. We evaluated the utility of AI-derived echocardiographic parameters on top of clinical variables in predicting outcomes post-AMI.

Methods: Consecutive AMI patients undergoing invasive coronary angiogram were included. Echocardiograms were analyzed using Us2.ai software. Independent predictors of one-year all-cause mortality and major adverse cardiac events (MACE) were assessed using Cox regression. Clinical, echocardiographic, and combined models were compared.

Results: Among 1001 patients, aged 64 years (54, 72) and predominantly male (78.1%), 161 (16.1%) died during follow-up. AI-echocardiographic markers independently associated with one-year all-cause mortality or MACE included lower LVEF, greater LV wall thickness, lower LV mass, greater LA area, lower LA reservoir strain and lower aortic valve area. For one-year mortality, the combined model demonstrated superior discrimination compared with the clinical model alone (AUC 0.85 vs. 0.81; $p = 0.018$). Similarly, for one-year MACE, the combined model showed improved discrimination compared with the clinical model (AUC 0.80 vs. 0.74; $p < 0.001$) and yielded the lowest Akaike's and Bayesian Informations.

Conclusion: Combining AI-derived echocardiographic parameters, together with traditional clinical risk factors, provides incremental prognostic value post-AMI. AI tools that automate complex assessments accurately and reproducibly may enhance risk stratification.

1. Introduction

Ischemic heart disease (IHD) remains one of the leading causes of mortality and morbidity worldwide, and global prevalence is increasing. (1) An acute myocardial infarction (AMI) is the most urgent presentation of IHD, requiring prompt therapy and accurate risk stratification. (2) Even with progress in treatments like percutaneous coronary intervention (PCI) and optimal secondary prevention measures, AMI patients still face a high risk of adverse clinical outcomes, including recurrent AMI and mortality.

Early prognostication of AMI patients enables patient-centered guidance on medical therapies, as well as personalized follow-up intensity and duration, aiding in clinical decision-making and cost-effective resource allocation. Conventional risk stratification methods, such as the GRACE score (3), usually employ a series of clinical and biochemical factors to predict the risk of adverse events but do not incorporate echocardiographic variables. (4) Echocardiography is routinely performed during AMI hospitalization and provides objective information on cardiac structure and function. As such, incorporating echocardiographic variables into risk prediction models has the

* Correspondence author at: 5 Hospital Drive, 169609, Singapore.
E-mail address: jonyap@yahoo.com (J. Yap).

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potential to enhance the accuracy of prediction of clinical outcomes in AMI patients. (5,6) Classically, the left ventricular ejection fraction (LVEF) was the primary echocardiographic predictor of clinical outcome after AMI. (7) However, LVEF provides only crude information on LV systolic function, with newer markers of both LV systolic and diastolic function emerging beyond LVEF. Echocardiographic variables like left atrial (LA) reservoir strain and ratio of early diastolic mitral inflow velocity to early diastolic mitral annulus velocity (E/e' ratio) have potential to more accurately predict clinical outcomes in AMI patients, independent of LVEF. (8–10)

Although these novel markers may be of additive value in risk stratification, they are not often part of standardized assessment, especially in low- and middle-income countries (LMIC) where resources may be scarce and correct execution and interpretation may be at stake. (11) Moreover, for various parameters, including the frequently measured LVEF, interobserver variability can jeopardize validity of the measurements. (12,13) In recent years, the emergence of artificial intelligence (AI) in echocardiography has gained attention. AI tools have the potential to analyze echocardiograms accurately, completely, and swiftly. (14,15)

The use of AI interpretation in an AMI population has not been well studied. We aim to evaluate the utility of clinical as well as AI-obtained echocardiographic parameters in predicting clinical outcomes in a contemporary Asian cohort of AMI patients undergoing PCI.

2. Methods

2.1. Study design and population

The Singapore Cardiac Databank (SCDB) registry is a national, prospective, observational registry of consecutive patients ≥21 years admitted for various cardiovascular diseases and/or procedures to all Singapore public hospitals. Detailed data collection such as demographics, clinical characteristics, investigations, procedural details, treatments, and discharge outcomes were captured in this registry. Details of the registry have been previously described. (16,17) In summary, trained coordinators collected data with the use of a standardized case report form and entered these findings into an electronic database, which are internally and externally validated. Registry participation was independent from medical care received. Consecutive patients who underwent PCI for acute myocardial infarction (ST-elevation myocardial infarction (STEMI) or non-STEMI) from a single tertiary cardiac institution in the registry from Jan 2018 to Jun 2019 were included. Patients were included if transthoracic echocardiography was performed during AMI admission. A waiver of ethical approval was obtained as analysis was performed on a de-identified dataset.

2.2. Definitions

Patients were followed up for at least one year and up to five years. The primary outcome was all-cause mortality at one-year. Secondary outcomes analyzed included one-year major adverse cardiac events (MACE), defined as cardiovascular mortality, AMI, and/or stroke; and overall all-cause mortality at one-to-five-year follow-up. These outcome data were obtained from national registries. We specifically focused on one-year and one-to-five-year outcomes, as the recommended outpatient follow-up time for uncomplicated AMI is one year. Therefore, we ought to investigate whether different predictors for events beyond one year are different. The estimated glomerular filtration rate (eGFR) was calculated according to the 2021 CKD-EPI formula. Significant coronary disease was defined as at least 50% stenosis in the left main (LM) branch, or at least 70% stenosis in the left anterior descending (LAD) branch, left circumflex (LCX) branch or right coronary artery (RCA).

2.3. Echocardiographic analysis

Transthoracic echocardiograms were performed by experienced sonographers during the index hospitalization, using commercially available ultrasound equipment (Philips and GE equipment). The echocardiograms were analyzed using the Us2.ai software (version 2, Us2.ai, Singapore), an FDA-cleared and CE-marked AI solution for interpreting echocardiograms, aiding both experienced and inexperienced medical professionals. The AI-automated measurements were shown to be interchangeable with human expert measurements at the Harvard/Brigham and Women's Hospital Echo Core Lab, and accurate across diverse datasets from Canada, Taiwan, and the US. (18–20)

The investigated parameters include both atrial and ventricular volumes, wall thickness and left ventricular mass, diastolic parameters, strain parameters and aortic valve parameters. If available, the biplane value of relevant echocardiographic variables was used. If unavailable, an apical four- or two-chamber view was used. For the E/e' ratio, the mean value was used. If unavailable, the lateral or septal value was taken.

2.4. Statistical analysis

Continuous variables with a normal distribution are presented as mean ± standard deviations, and continuous variables with a skewed distribution are presented as median (interquartile range). Binary and categorical variables are presented as numbers (percentages). Group comparisons were made using student *t*-test, Mann-Whitney *U* test or Chi-Square test, as appropriate. Variables of interest were imputed using the multiple imputation by chained equations method, with 50 imputed databases. Data on missing variables is presented in *Table S1*. The date of in-hospital outcomes was imputed at 7 days after the PCI date. Predictors for all-cause mortality and MACE were studied in Cox regression analyses, using all available medical history, periprocedural and echocardiographic variables. A clinical, echocardiographic, and combined model using all available clinical and echocardiographic variables were made. For each model, univariable Cox regression was performed for every candidate variable, and variables with a *p*-value below 0.1 were carried forward into multivariable analysis. Within the multivariable model, backward stepwise selection was performed, removing the variable with the highest *p*-value above 0.05 at each step, until only variables with $p < 0.05$ remained, to arrive at the final prediction model. Variables with pearson $|R| \geq 0.7$ were excluded to address collinearity, and the variable with the strongest univariable association with the outcome was retained while the other was excluded. A two-sided *p*-value of 0.05 was considered significant. Statistical analyses were performed using Stata version 18.0 MP (StataCorp, College Station, United States) and R version 4.5.1 (R Foundation for Statistical Computing, Vienna, Austria).

3. Results

3.1. Patient characteristics

We included 1001 allcomers AMI patients. Baseline characteristics of our population are shown in Table 1. During the follow-up period of 4.2 years (3.8, 4.6), 161 (16.1%) died, with 92 (9.2%) from a cardiovascular cause. Fifteen (1.5%) had a repeat AMI, and eighteen (1.8%) experienced a stroke within one-year follow-up. Patients that died were older and were more often females. There was a significantly higher prevalence of cardiovascular risk factors and known cardiovascular disease, as well as more renal and obstructive lung disease. Importantly, patients with non-STEMI, left main or multivessel disease had worse survival.

The majority of patients had their echocardiogram exam performed on the day of or the day after PCI (633 patients, 63.2%). Some patients had their echocardiogram performed before the PCI date (148 patients, 14.8%); nearly all these patients had a non-STEMI (143 patients).

Table 1
Clinical characteristics.

	Alive (n = 840)	Dead (n = 161)	p-value
Age, years	62 (53, 70)	72 (61, 80)	<0.001
Male gender	673 (80.1%)	109 (67.7%)	<0.001
Body mass index, kg/m^2	25.5 (23.1, 28.7)	24.5 (21.5, 28.1)	0.010
Race			0.46
Chinese	534 (63.6%)	103 (64.0%)	
Indian	143 (17.0%)	33 (20.5%)	
Malay	104 (12.4%)	18 (11.2%)	
Others	59 (7.0%)	7 (4.3%)	
Diabetes mellitus	268 (31.9%)	101 (62.7%)	<0.001
Hypertension	495 (58.9%)	127 (78.9%)	<0.001
Dyslipidemia	509 (60.6%)	114 (70.8%)	0.014
Current smoker	269 (32.0%)	32 (19.9%)	0.002
Prior AMI	116 (13.8%)	45 (28.0%)	<0.001
Prior PCI	149 (17.7%)	54 (33.5%)	<0.001
Prior CABG	43 (5.1%)	16 (9.9%)	0.017
Prior heart failure	3 (0.4%)	13 (8.1%)	<0.001
Atrial fibrillation	28 (3.3%)	14 (8.7%)	0.002
Cerebrovascular disease	48 (5.7%)	26 (16.1%)	<0.001
Peripheral arterial disease	15 (1.8%)	17 (10.6%)	<0.001
Renal failure requiring dialysis	17 (2.0%)	36 (22.4%)	<0.001
Chronic lung disease	11 (1.3%)	10 (6.2%)	<0.001
STEMI presentation	428 (51.0%)	58 (36.0%)	<0.001
Femoral access site	206 (24.5)	114 (70.8)	<0.001
Multivessel disease			
Significant LM disease (≥50% stenosis)	87 (10.4%)	42 (26.1%)	<0.001
Significant LAD disease (≥70% stenosis)	615 (73.2%)	131 (81.4%)	0.030
Significant LCX disease (≥70% stenosis)	434 (51.7%)	110 (68.3%)	<0.001
Significant RCA disease (≥70% stenosis)	496 (59.0%)	118 (73.3%)	<0.001
Coronary anatomy			<0.001
SVD without LM disease	329 (39.5)	33 (20.6)	
MVD without LM disease	416 (50.0)	85 (53.1)	
LM disease	87 (10.5)	42 (26.2)	
Percutaneous coronary intervention attempted in:			
LM	51 (6.1%)	31 (19.3%)	<0.001
LAD	429 (51.1%)	92 (57.1%)	0.16
LCX	243 (28.9%)	56 (34.8%)	0.14
RCA	334 (39.8%)	68 (42.2%)	0.56
>1 vessel PCI attempt	171 (20.4)	62 (38.4)	<0.001
Troponin T pre-PCI, ng/L	145 (45, 614)	472 (109, 1850)	<0.001
eGFR, ml/min/1.73m^2	88.0 (70.8, 103.0)	48.5 (20.3, 72.0)	<0.001
Hemoglobin, g/dl	14.3 (12.9, 15.4)	12.3 (10.7, 14.2)	<0.001

CABG: coronary artery bypass grafting, MVD: multivessel disease, SVD: single vessel disease.

Table 2
AI-derived echocardiography parameters.

	Alive (n = 840)	Dead (n = 161)	p-value
LVEF, %	56.7 (48.8, 63.6)	46.9 (35.6, 57.6)	<0.001
LVEDV, ml	73.1 (59.7, 88.4)	78.0 (63.8, 102.3)	0.002
LVESV, ml	30.9 (23.5, 42.0)	40.3 (27.1, 61.4)	<0.001
IVSd, mm	9.9 (8.9, 11.3)	10.0 (9.0, 11.2)	0.65
LVPWd, mm	9.4 (8.6, 10.5)	10.1 (9.1, 11.4)	<0.001
RWT, %	0.4 (0.4, 0.5)	0.5 (0.4, 0.5)	0.005
LV mass, g	139.6 (117.7, 168.5)	155.7 (125.0, 181.1)	0.001
LV GLS, %	−16.3 ± 4.7	−13.1 ± 5.2	<0.001
E/A ratio	1.0 ± 0.4	1.0 ± 0.4	0.40
E/e' ratio	9.2 (7.3, 11.7)	13.4 (10.3, 17.6)	<0.001
e' septal, cm/s	6.1 (5.0, 7.6)	4.9 (3.9, 5.9)	<0.001
e' lateral, cm/s	7.8 (6.3, 9.7)	6.3 (5.0, 7.8)	<0.001
RVESV, ml	11.0 (7.7, 16.4)	11.6 (8.1, 18.4)	0.062
RVEDV, ml	24.8 (17.4, 33.1)	24.4 (18.2, 34.1)	0.86
TAPSE, mm	20.3 ± 4.1	19.4 ± 4.8	0.026
TR Vmax, cm/s	2.3 (2.0, 2.5)	2.5 (2.0, 2.8)	0.002
RV GLS, %	−17.9 ± 6.8	−15.5 ± 7.1	<0.001
S' septal, cm/s	6.9 (5.8, 8.0)	5.8 (4.7, 7.3)	<0.001
S' lateral, cms	7.9 (6.5, 9.6)	6.3 (4.9, 8.0)	<0.001
LA area, mm^2	15.8 (13.7, 18.1)	17.1 (14.3, 20.2)	<0.001
LAESV, ml	38.6 (30.9, 46.4)	42.7 (33.6, 56.8)	<0.001
LA reservoir strain, %	26.0 (19.2, 34.6)	18.0 (11.9, 23.7)	<0.001
RAESV, ml	24.8 (19.1, 33.0)	25.1 (19.7, 32.2)	0.94
RA area, mm^2	11.4 (9.7, 13.6)	11.4 (9.9, 13.3)	0.87
AVA, mm^2	2.5 ± 0.7	2.1 ± 0.8	<0.001
AoV Vmax, cm/s	1.2 (1.1, 1.4)	1.4 (1.1, 1.6)	<0.001
AoV Pmean, mmHg	3.3 (2.6, 4.4)	4.2 (2.7, 5.7)	<0.001

AVA: aortic valve area, AoV Pmax: peak pressure over the aortic valve, AoV Vmax: peak velocity of the aortic valve, e': early diastolic mitral annular velocity, E/A ratio: mitral ratio of peak early to late diastolic filling velocity, GLS: global longitudinal strain, IVSd: interventricular septal diameter, LAESV: left atrial end systolic volume, LVEDV: left ventricular end diastolic volume, LVESV: left ventricular end systolic volume, RVEDV: right ventricular end diastolic volume, RVESV: right ventricular end systolic volume, RA: right atrial, RAESV: right atrial end systolic volume, RWT: relative wall thickness, s': tricuspid annulus peak systolic velocity, TAPSE: tricuspid annular plane systolic excursion, TR Vmax: maximal tricuspid regurgitation velocity.

Results of the AI echocardiographic analysis are presented in Table 2. Importantly, patients who died had a significantly lower LVEF, as well as greater ventricular and atrial volumes. Furthermore, these patients had significantly reduced right ventricular (RV) function and reduced LV diastolic function. In addition, all the strain variables (LV GLS, RV GLS, and LA reservoir strain) were significantly reduced in the mortality group.

3.2. Predictors for clinical outcome

Independent predictors for all-cause mortality and MACE are depicted in Table 3. Independent clinical predictors for one-year mortality include pre-existing heart failure, peripheral arterial disease, current dialysis, chronic lung disease, LM disease, higher troponin levels and poorer kidney function. Independent echocardiographic predictors for one-year mortality include lower LVEF, lower LA reservoir strain, and lower AVA. Independent predictors for one-year mortality in a combined model include pre-existing heart failure, peripheral arterial disease, LM disease, poorer kidney function, lower LVEF, lower LA reservoir strain, lower LV mass, and high aortic gradient.

Independent clinical predictors for one-to-five years mortality include higher age, diabetes mellitus, pre-existing heart failure, peripheral arterial disease, current dialysis, chronic lung disease and poorer kidney function. Independent echocardiographic predictors for one-to-five years mortality include higher E/e' ratio, higher LA area, lower LA reservoir strain and higher TR V_{max}. Independent predictors for one-to-five-year mortality in a combined model include higher age, diabetes mellitus, pre-existing heart failure, peripheral arterial disease, current dialysis, chronic lung disease, poorer kidney function, higher LV volume, greater LV wall thickness, and lower LV mass.

Independent clinical predictors for one-year MACE include diabetes mellitus, pre-existing heart failure, higher troponin levels and poorer kidney function. Independent echocardiographic predictors for one-year MACE include lower LVEF, greater LV wall thickness, lower LV mass, greater LA area, lower LA reservoir strain, and lower AVA. Independent predictors for one year MACE in a combined model include diabetes mellitus, poorer kidney function, lower LVEF, lower LA reservoir strain, and lower AVA. Univariate regression results are depicted in the *Supplementary materials*.

3.3. Comparison of model performance

Performance metrics for each of the models and outcomes are depicted in *Table* 4. For one-year mortality, the clinical model demonstrated good discriminative performance with an AUC of 0.81 (95% CI 0.76–0.86), which was comparable to the echocardiographic model

Table 3
Clinical, echocardiographic and combined models for outcomes.

One-year mortality						
	Clinical model		Echocardiographic model		Combined model	
	HR (95% CI)	p-value	HR (95% CI)	p-value	HR (95% CI)	p-value
Pre-existing heart failure	3.983 (1.867, 8.495)	<0.001			2.232 (1.051, 4.741)	0.037
Peripheral arterial disease	3.136 (1.661, 5.922)	<0.001			2.085 (1.119, 3.887)	0.021
Current dialysis	0.401 (0.198, 0.823)	0.013				
Chronic lung disease	3.217 (1.354, 7.646)	0.009				
Multivessel disease*:						
MVD without LM disease	1.540 (0.783, 3.026)	0.21			1.451 (0.745, 2.828)	0.27
LM disease	2.909 (1.410, 6.002)	0.004			2.197 (1.072, 4.501)	0.032
Troponin/100 (ng/l)	1.010 (1.003, 1.017)	0.005				
eGFR (ml/min/1.73m^2)	0.975 (0.966, 0.984)	<0.001			0.984 (0.976, 0.991)	<0.001
LVEF (%)			0.944 (0.928, 0.961)	<0.001	0.943 (0.924, 0.961)	<0.001
LA reservoir strain (%)			0.958 (0.934, 0.982)	0.001	0.961 (0.936, 0.987)	0.004
AVA (mm^2)			0.522 (0.370, 0.737)	<0.001		
LV mass (g)					0.994 (0.988, 0.999)	0.028
AoV P_{mean} (mmHg)					1.049 (1.017, 1.082)	0.003
One-to-five years mortality						
	Clinical model		**Echocardiographic model**		**Combined model**	
	HR (95% CI)	p-value	HR (95% CI)		HR (95% CI)	p-value
Age (y)	1.058 (1.036, 1.080)	<0.001			1.068 (1.045, 1.092)	<0.001
Diabetes mellitus	1.712 (1.093, 2.680)	0.019			1.861 (1.184, 2.927)	0.008
Pre-existing heart failure	3.504 (1.572, 7.808)	0.002			4.114 (1.840, 9.195)	<0.001
Peripheral arterial disease	2.363 (1.275, 4.381)	0.007			2.141 (1.150, 3.986)	0.017
Current dialysis	3.152 (1.571, 6.234)	0.001			3.248 (1.591, 6.632)	0.001
Chronic lung disease	3.368 (1.423, 7.973)	0.006			3.742 (1.560, 8.974)	0.004
eGFR (ml/min/1.73m^2)	0.982 (0.972, 0.991)	<0.001			0.985 (0.975, 0.995)	0.003
E/e' ratio			1.050 (1.027, 1.093)	<0.001		
LA area (mm^2)			1.054 (1.004, 1.107)	0.033		
LA reservoir strain (%)			0.972 (0.952, 0.993)	0.009		
TR V_{max} (cm/s)			1.736 (1.145, 2.631)	0.010		
LVEDV (ml)					1.017 (1.008, 1.025)	<0.001
LVPWd (mm)					1.216 (1.053, 1.403)	0.008
LV mass (g)					0.992 (0.983, 1.000)	0.044
One-year MACE						
	Clinical model		**Echocardiographic model**		**Combined model**	
	HR (95% CI)	p-value	HR (95% CI)	p-value	HR (95% CI)	p-value
Diabetes mellitus	2.160 (1.340, 3.480)	0.002			2.064 (1.293, 3.292)	0.003
Pre-existing heart failure	3.010 (1.386, 6.919)	0.006				
Troponin/100 (ng/l)	1.007 (1.001, 1.012)	0.017				
eGFR (ml/min/1.73m^2)	0.987 (0.980, 0.993)	<0.001			0.990 (0.984, 0.998)	0.010
LVEF (%)			0.943 (0.926, 0.961)	<0.001	0.955 (0.938, 0.972)	<0.001
LVPWd (mm)			1.237 (1.075, 1.424)	0.003		
LV mass (g)			0.992 (0.986, 1.000)	0.039		
LA area (mm2)			1.071 (1.012, 1.134)	0.017		
LA reservoir strain (%)			0.974 (0.951, 0.997)	0.048	0.972 (0.950, 0.995)	0.019
AVA (mm2)			0.713 (0.510, 0.996)	0.048	0.709 (0.515, 0.976)	0.036

* Baseline factor is SVD without LM disease.

(AUC 0.81, 95% CI 0.75–0.85). Addition of echocardiographic variables to the clinical model resulted in a significant improvement in discrimination, with the combined model achieving an AUC of 0.85 (95% CI 0.81–0.89; DeLong test $p = 0.018$). This improvement was further supported by lower AIC and BIC values, indicating superior model fit.

For one-to-five-year mortality, the clinical model yielded an AUC of 0.85 (95% CI 0.81–0.88), whereas the echocardiographic model showed lower discriminative ability (AUC 0.73, 95% CI 0.67–0.78). The combined model demonstrated the highest discrimination with an AUC of 0.86 (95% CI 0.83–0.89), representing a statistically significant improvement over the clinical model alone (DeLong test $p = 0.008$), and again showed the most favorable AIC and BIC values.

For one-year MACE, the clinical model achieved an AUC of 0.74 (95% CI 0.68–0.79). The echocardiographic model demonstrated improved discrimination (AUC 0.78, 95% CI 0.72–0.83). Combining clinical and echocardiographic variables resulted in a further significant increase in predictive performance, with the combined model yielding an AUC of 0.80 (95% CI 0.74–0.85; DeLong test $p < 0.001$), accompanied by the lowest AIC and BIC values among the evaluated models.

4. Discussion

Even in the era with advanced invasive and medical treatment options, there is a subset of AMI patients that continue to have a poorer prognosis and identification of such a group may aid in optimizing resources and therapy. In our study with 1001 all-comer AMI patients, we showed that both established risk factors and novel echocardiographic parameters, assessed through AI, are of additive value in the prediction of clinical outcomes after AMI.

We found several relatively novel echocardiographic parameters that were predictive of adverse clinical outcomes in AMI patients. Strain measurements have emerged as a powerful measure of cardiac function, capturing both contraction and relaxation ability, as well as being a strong predictor of clinical outcomes. (21) LA reservoir strain was found

Table 4
Performance metrics for clinical, echocardiographic and combined models for outcomes.

	AUC	p-value	AIC	BIC
One-year mortality				
Clinical model	0.81 (0.76, 0.86)	0.018	1059.22	1078.66
Echocardiographic model	0.81 (0.75, 0.85)		1047.08	1054.38
Combined model	0.85 (0.81, 0.89)		1016.66	1038.53
One-to-five-year mortality				
Clinical model	0.85 (0.81, 0.88)	0.008	1244.51	1263.22
Echocardiographic model	0.73 (0.67, 0.78)		1372.49	1383.18
Combined model	0.86 (0.83, 0.89)		1234.73	1261.45
One-year MACE				
Clinical model	0.74 (0.68, 0.79)	<0.001	1173.48	1184.43
Echocardiographic model	0.78 (0.72, 0.83)		1139.29	1154.22
Combined model	0.80 (0.74, 0.85)		1126.36	1138.80

to be independently associated with both mortality and MACE. LA reservoir strain is also a measure of myocardial deformation, but during the LA filling phase. It has the advantage over LA volumes to be less load dependent. (22) It has been shown to be a more sensitive marker to determine the diagnosis of heart failure than left atrial volume. (23) Importantly, LA reservoir strain has been linked to clinical outcomes in AMI patients priorly. (8,24) In our study, LA strain was an independent predictor of outcomes from the multivariate analysis. Importantly, many of the independently predictive echocardiographic variables are, at least in part, diastolic function parameters. This fuels the hypothesis that besides systolic adverse remodeling, also diastolic remodeling plays a role in post-AMI prognosis. Many of these variables, including E/e' ratio and LVWPd, are often used in the diagnosis of heart failure with preserved ejection fraction (HFpEF). (25) It can be hypothesized that this may also contribute to adverse outcomes in AMI patients, although there is still limited data on HFpEF in the context of AMI. (26)

Emerging evidence suggests that excessively high LVEF may also identify patients at increased cardiovascular risk. In a multicenter cohort of patients hospitalized for decompensated HFpEF, a higher LVEF was associated with an unfavourable prognosis (27), and in elderly patients with HFpEF, supranormal LVEF (≥65%) has been linked to a distinct clinical and echocardiographic profile compared with normal LVEF (28). These findings suggest that very high LVEF values may not simply reflect superior cardiac performance, but could instead mark a separate, higher risk subgroup. Exploring more flexible, nonlinear modeling of LVEF in future analyses, possibly aided by automated echocardiographic measurement tools, could help refine risk prediction after AMI.

In this study, we showed that traditional variables such as LVEF and LV mass, but also more novel parameters such as strain wall thickness and strain parameters have incremental value in predicting clinical outcomes in AMI patients. These parameters, especially strain, are not routinely analyzed in all centers and may also require additional time-consuming effort and expertise to perform the measurements. Furthermore, there is known inter-observer variability. (13) AI-based analysis offers a potential option to have objective and accurate strain measurements performed, even without local available expertise. Besides offering accurate annotation, especially in areas where expertise may not be available, both intra- and interobserver variabilities may also be improved compared to human interpretation. (18,29) This will allow improved reproducible and cost-effective echocardiographic assessment, especially with increasing demand for non-invasive cardiac imaging. (30)

With regards to the traditional clinical predictors identified, there has been a wealth of existing evidence. Diabetes presents a large global challenge, given its great burden and health care and persistent association with poor outcomes. (31) Kidney function was the variable consistently associated with worse clinical outcomes. It is well established that even minor deterioration in renal function is associated with poorer outcomes post-AMI. (32) Risk factors for some of these conditions are modifiable, further stressing the need for adequate patient education and optimal primary and secondary prevention.

Strengths of our study include our unselected, consecutive, multi-ethnic patient population. In addition, through AI analysis, the wide spectrum of echocardiographic variables were largely available for analysis. Limitations include the retrospective study design and its attendant limitations. Not all confounders may be able to be fully adjusted for despite multivariate analysis. Secondly, only AMI patients undergoing invasive therapy were included, and data on those undergoing medical therapy was not available in the registry. Thirdly, patients who did not have an echocardiogram performed during the index hospitalization were excluded. Although a small group, some patients had their echocardiogram performed before the PCI procedure, which may have an impact on the results. A limitation of this study is that the prediction models were derived and assessed in a single cohort, without external validation. As such, the reported AUC, AIC, and BIC reflect performance within this cohort, and validation in an independent population represents an important next step to confirm the generalizability of these models. We consider this a valuable direction for future research, building on the framework established here. Lastly, sequential changes in echocardiographic parameters were not available currently. This may be particularly important for longer term outcomes and will also be work for further research.

5. Conclusion

A combination of AI-derived echocardiographic parameters, together with traditional clinical risk factors, in AMI patients undergoing PCI provides incremental prognostic value than either alone. Beyond established echocardiographic parameters, contemporary AI-assessed LA strain was an independent predictor of outcomes. AI tools that automate complex assessments accurately and reproducibly may enhance risk stratification of post-AMI adverse outcomes.

All authors takes responsibility for all aspects of the reliability and freedom from bias of the data presented and their discussed interpretation.

CRediT authorship contribution statement

Chris Lenselink: Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Yee How Lau:** Writing – review & editing, Formal analysis, Data curation. **Weiting Huang:** Writing – review & editing, Supervision. **See Hooi Ewe:** Writing – review & editing, Supervision. **Siau Chien Chiong:** Writing – review & editing, Supervision. **Choon Ta Ng:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Kim Ricken:** Writing – review & editing, Visualization, Supervision, Methodology, Data curation, Conceptualization. **Erik Lipsic:** Writing – review & editing, Supervision, Conceptualization. **Adriaan Voors:** Writing – review & editing, Supervision. **Carolyn Su Ping Lam:** Writing – review & editing, Supervision, Software. **Khung Keong Yeo:** Writing – review & editing, Supervision. **Jonathan Yap:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization.

Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijcard.2026.134638.

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