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Healthcare Big Data in Hong Kong: Development and implementation of artificial intelligence-enhanced predictive models for risk stratification

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ABSTRACT

Routinely collected electronic health records (EHRs) data contain a vast amount of valuable information for conducting epidemiological studies. With the right tools, we can gain insights into disease processes and development, identify the best treatment and develop accurate models for predicting outcomes. Our recent systematic review has found that the number of big data studies from Hong Kong has rapidly increased since 2015, with an increasingly common application of artificial intelligence (AI). The advantages of big data are that i) the models developed are highly generalisable to the population, ii) multiple outcomes can be determined simultaneously, iii) ease of cross-validation by for model training, development and calibration, iv) huge numbers of useful variables can be analyzed, v) static and dynamic variables can be analyzed, vi) non-linear and latent interactions between variables can be captured, vii) artificial intelligence approaches can enhance the performance of prediction models. In this paper, we will provide several examples (cardiovascular disease, diabetes mellitus, Brugada syndrome, long QT syndrome) to illustrate efforts from a multi-disciplinary team to identify data from different modalities to develop models using territory-wide datasets, with the possibility of real-time risk updates by using new data captured from patients. The benefit is that only routinely collected data are required for developing highly accurate and high-performance models. AI-driven models outperform traditional models in terms of sensitivity, specificity, accuracy, area under the receiver operating characteristic and precision-recall curve, and F1 score. Web and/or mobile

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Table 1
Comparisons of different risk models based on Asian (including Chinese) cohorts for predicting adverse outcomes.

Disease	Cohort size for model development	Variables	Method(s)	Outcomes	Ref
ASCVD					
Chinese-PAR by Yang *et al.* (2016)	21,320	Age, treated or untreated SBP, total cholesterol, HDL-C, current smoking, and diabetes mellitus, waist circumference, geographic region, urbanisation, and family history of ASCVD	Cox regression	10-year ASCVD risk (sex-specific)	4
PowerAI-CVD by Li *et al.* (2023)	154,569	Age, sex, mean SBP, mean DBP, existing cardiovascular diseases, medications (anticoagulants, antiplatelets, antihypertensive drugs, and statins) and laboratory tests (NLR, creatinine, ALP, AST, ALT, HbA1c, fasting glucose, TG, LDL-C and HDL-C	CatBoost, XGBoost, Gradient Boosting, Multilayer Perceptron, Random Forest, Naïve Bayes, Decision Tree, k-Nearest Neighbor, AdaBoost, SVM-Sigmod	MACE, composite of myocardial infarction, heart failure, TIA/stroke, cardiovascular mortality	3
Diabetes					
Cho *et al.* (2008)	292	Onset age, diabetes duration, age, sex, WBC, haemoglobin, platelet count, cholesterol, AST, ALP, BUN, Creatinine, Uric acid, Na, K+, TG, HDL-C, LDL-C, HbA1C, Microalbumin, SBP, DBP, BMI	Logistic regression, SVM, and SVM with a cost sensitive learning method	Diabetic nephropathy	13
Shi *et al.* (2020)	4,219	Disease course, BMI, TG, SBP, postprandial blood glucose (PBG), HbA1c, and BUN	LASSO regression, logistic regression	Diabetic nephropathy and diabetic retinopathy	7
Liu *et al.* (2020)	Not reported	39 features including age and gender, 13 items related to the urine test, HbA1c and 23 items related to the biochemical test	Bayesian network model, bootstrap and Tabu search algorithm, Markov blanket, decision tree, Naïve Bayes, random forest and C5.0	Diabetic nephropathy, retinopathy, diabetic foot, macrovascular complications, peripheral neuropathy and DKA	8
Wang *et al.* (2021)	1,610	Age, HbA1c, direct bilirubin, creatinine, GGT, ALT, glucose, total bilirubin, Mg, total protein, IP, uric acid, HDL-C, AST, CO2, calcium, ALP, LDH, Urea, chloride, Sex, LDL-C, TC, TG, ALB, K, Na, creatine kinase	SVM models (BR, RankSVM, and WML-SSLM), ML-KNN, ML-RBF, and BP-MLL	Macrovascular and microvascular complications, neuropatjhy	9
PowerAI-Diabetes by Lee *et al.* (2021)	25,186	Age, baseline diseases, hypoglycaemia, visit-to-visit variability and mean in TG, HbA1c, total cholesterol, HDL-C, LDL-C, anti-diabetic medications	Random survival forest	Neurological complications, ophthalmological complications, CKD, dementia, osteoporosis, peripheral vascular disease, ischemic heart disease, atrial fibrillation and heart failure, and mortality	10
Fan *et al.* (2021)	185	Age, duration of diabetes (≥1 year), duration of unadjusted hypoglycemic treatment (≥1 year), number of insulin species, total cost (total expenditure during hospitalization) of hypoglycemic drugs, and number of hypoglycemic drugs (which were computed as continuous variables) and gender, genetic history of diabetes, and dyslipidemia	ensemble model, artificial neural network, classification and regression tree, quick unbiased efficient statistical tree, discriminate and Bayesian network	Diabetic nephropathy, angiopathy, peripheral neuropathy and eye disease	11
Lee *et al.* (2021)	273,678	Age, gender, baseline comorbidities, anemia, mean values of neutrophil-to-lymphocyte ratio, HDL-c, total cholesterol, TG, HbA1c, fasting blood glucose (FBG), measures of variability of both HbA1c and FBG	Cox regression, RSF, DeepSurv	Mortality	12
Brugada syndrome					
PowerAI-Brugada, Lee *et al.* (2021)	548	Spontaneous type 1 Brugada pattern, family history of SCD, syncope, initial VT/VF, non-ventricular arrhythmias (AT, AF, SVT), ER pattern on peripheral leads, aVR sign, S-wave in lead I, QTc ≥ 436 ms	Risk score from Cox regression, RSF, Ada boost classifier, Gaussian naïve Bayes, light gradient boosting machine, random forest classifier, gradient boosting classifier and decision tree classifier	Sustained VT/VF	18
Nakamura *et al.* (2023)	157	All ECG features	deep neural network using the Keras framework with a TensorFlow	VF	31
Long QT syndrome					
Chen *et al.* (2021)	327	cancer diagnosis, serum potassium and calcium levels combined with ECG features	RSF	All-cause mortality	20
PowerAI-LQTS by Lee *et al.* (2021)	121	Age of diagnosis, syncope, VT/VF, the presence of PVCs	Cox regression, RSF	Spontaneous VT/VF	22

versions of the risk models allow clinicians to risk stratify patients quickly in clinical settings, thereby enabling clinical decision-making. Efforts are required to identify the best ways of implementing AI algorithms on the web and mobile apps.

Introduction

Routinely collected electronic health records (EHRs) data contain a vast amount of valuable information for conducting epidemiological studies. With the right tools, we can gain insights into disease processes and development, identify the best treatment and develop accurate models for predicting outcomes. Our recent systematic review has found that the number of big data studies from Hong Kong has rapidly increased since 2015[1] with an increasingly common application of artificial intelligence (AI). The advantages of big data are that i) the models developed are highly generalisable to the population, ii) multiple outcomes can be determined simultaneously, iii) ease of cross-validation by for model training, development and calibration, iv) huge numbers of useful variables can be analyzed, v) static and dynamic variables can be analyzed, vi) non-linear and latent interactions between variables can be captured, vii) artificial intelligence approaches can enhance the performance of prediction models. In this paper, we will provide several examples to illustrate efforts from a multi-disciplinary team to identify data from different modalities to develop models using territory-wide datasets (Table 1), with the possibility of real-time risk updates by using new data captured from patients.

PowerAI-CVD

Our team was the first in Hong Kong to develop an AI model for predicting mortality in patients with a history of myocardial infarction[2]. Earlier this year, we developed PowerAI-CVD, which is the first-in-world, Chinese-specific, AI-driven, comprehensive predictive model incorporating physiological BP measurements, disease status, medications and laboratory tests for 10-year CVD risk[3]. This was developed using a population-wide dataset of >150,000 patients from the community, attending family medicine clinics in the public sector of Hong Kong. The dashboard for this prediction tool is detailed in Fig. 1. To facilitate ease of implementation, we further developed ChineseCVD, the first-in-world, web-based Chinese-specific Cardiovascular Risk Calculator incorporating the impact of long COVID, COVID-19 vaccination, SGLT2i and PCSK9i treatment effects, but without AI. In the future, we aim to combine both PowerAI-CVD and ChineseCVD to further improve the performance of our model whilst maintaining accessibility through web-based or mobile-based platforms. Currently, there are only China-PAR (Prediction for atherosclerotic CVD Risk in China)[4] and absolute risk score model from the Japan Arteriosclerosis Longitudinal Study (JALS)[5] for Chinese and Japanese users, respectively.

PowerAI-Diabetes

PowerAI-Diabetes is the third-in-world, Chinese-specific AI-driven predictive model for predicting diabetic complications (Fig. 2). A previous systematic review published in 2022 identified 11 studies which reported on model development for predicting diabetic complications[6]. Of these, five studies focused specifically on Chinese populations. Shi *et al.* in April 2020 described a nomogram model

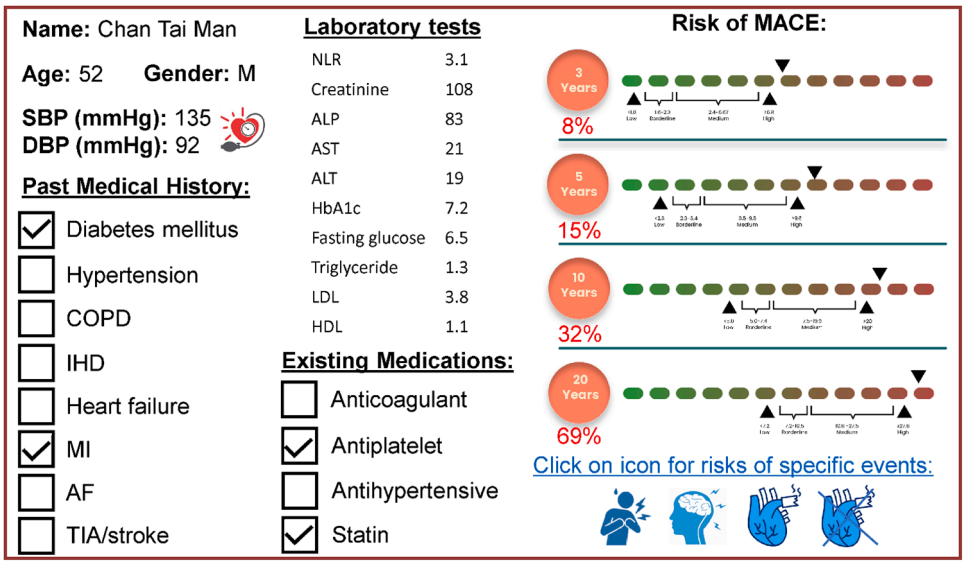

Fig. 1. PowerAI-CVD (2023), the first-in-world, Chinese-specific, AI-driven, comprehensive predictive model incorporating physiological BP measurements, disease status, medications and laboratory tests for 10-year CVD risk. Reproduced from[3] with permission.

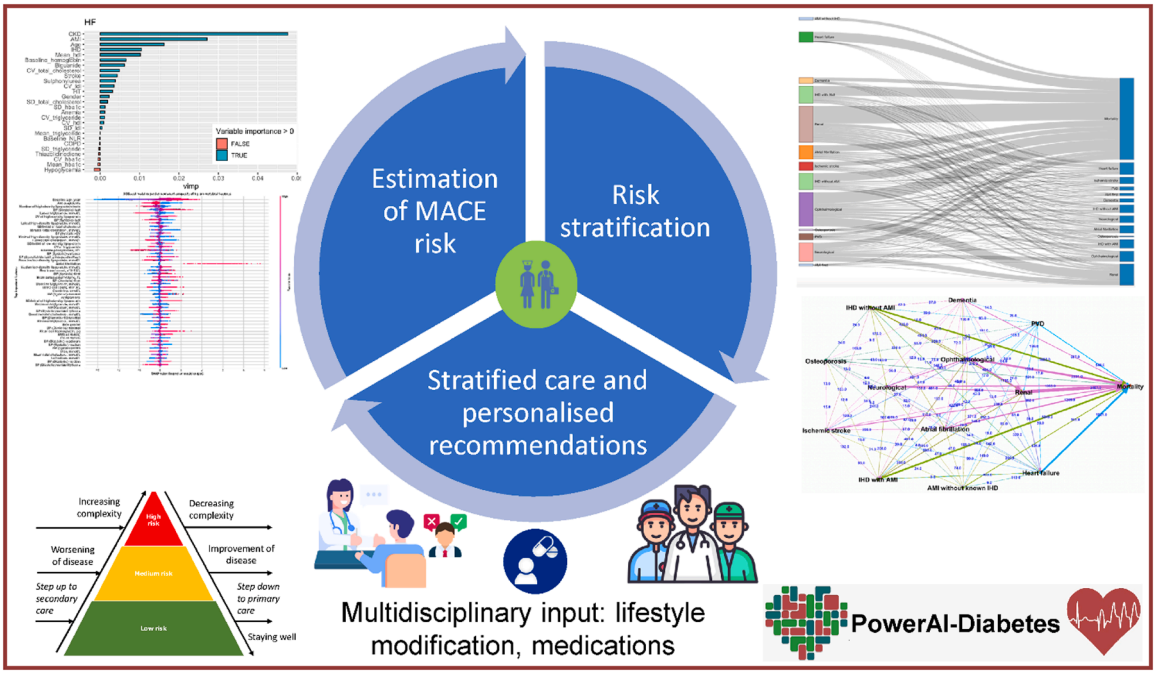

Fig. 2. PowerAI-Diabetes (2021), the third-in-world, Chinese-specific AI-driven predictive model for predicting diabetic complications and first-in-world to incorporate lipid and glycaemic variability with AI. Our model can accurately predict 9 different diabetes-related complications (neurological, ophthalmological, CKD, dementia, osteoporosis, peripheral vascular disease, ischemic heart disease, atrial fibrillation and heart failure).

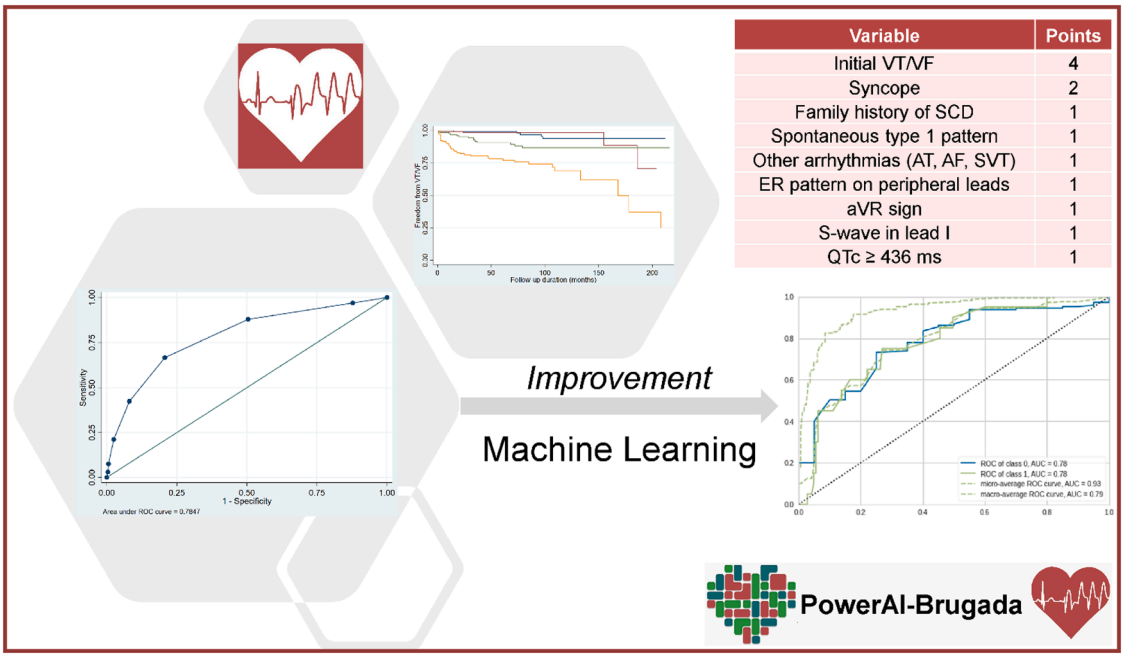

Fig. 3. PowerAI-Brugada (2021), the first in world, AI-driven, comprehensive predictive model incorporating genetics, clinical findings and ECG features for predicting ventricular arrhythmias and sudden cardiac death in Brugada syndrome. Adapted from[18] with permission.

for predicting diabetic nephropathy and retinopathy using LASSO and logistic regression[7]. Liu *et al.* reported in May 2020 a Bayesian network model, bootstrap and Tabu search algorithm, Markov blanket, decision tree, Naïve Bayes, random forest and C5.0 for warning factors of diabetic complications[8]. Wang *et al.* proposed in August 2020 weighted multi-label small sphere and large margin machine (SSLM), constructed by introducing the binary relevance to SSLM[9]. Lee *et al.* in May 2021 described multiple models for predicting

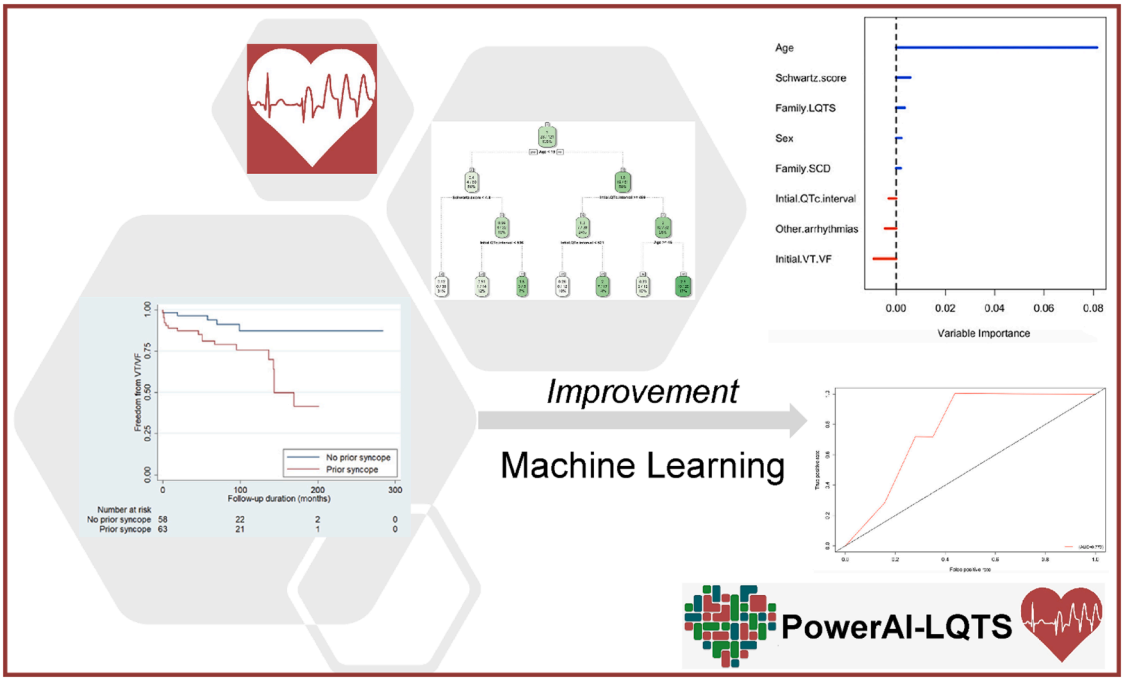

Fig. 4. PowerAI-LQTS (2021), the first in world, AI-driven, comprehensive predictive model incorporating genetics, clinical findings and ECG features for predicting ventricular arrhythmias and sudden cardiac death in long QT syndrome.

complications (neurological, ophthalmological, CKD, dementia, osteoporosis, peripheral vascular disease, ischemic heart disease, atrial fibrillation and heart failure) and mortality in diabetes mellitus using machine learning[10]. Fan *et al.* reported in June 2021 the application of ensemble model, artificial neural network, classification and regression tree, quick unbiased efficient statistical tree, discriminate and Bayesian network for predicting diabetic nephropathy, peripheral neuropathy, angiopathy, eye disease, and glycosylated hemoglobin A[11]. Our team was also first-in-world to incorporate lipid and glycemic variability into an AI-driven predictive model, using random survival forest[10]. Using an expanded cohort of 273,678 subjects, we further explored Cox proportional hazards DeepSurv, a deep feed-forward neural network technique incorporating traditional Cox regression, demonstrating improvement in the performance compared to regression without neural network[12]. From Liu *et al.*[8] we also found a study from 2008 which applied several AI methods in a small cohort of diabetic patients but in Koreans[13].

PowerAI-Brugada and PowerAI-LQTS

Inherited arrhythmic syndromes represent a range of congenital disorders from cardiac ion channelopathies to cardiomyopathies, which predispose to the development of sudden cardiac death. AI is increasingly used to facilitate diagnosis using ECGs[14]. The application of AI for the diagnosis and management of inherited arrhythmic syndromes has recently been described in a review[15]. In 2021, our team developed PowerAI-Brugada and PowerAI-LQTS, the first-in-world, AI-driven, comprehensive predictive model incorporating genetics, clinical findings and ECG features for predicting ventricular arrhythmias and sudden cardiac death in Chinese patients with Brugada syndrome and long QT syndrome (LQTS) (Figs. 3 and 4).

On Brugada syndrome, our team was first-in-world to report that the consideration of latent variables using non-negative matrix factorisation (NMF) can enhance risk prediction[16]. We extended this work by developing a model that combined both RSF and NMF, outperforming models that used either technique alone, for predicting ventricular tachyarrhythmias and sudden cardiac death, achieving 0.87, 0.89 and 0.88 for precision, recall and F1 score, respectively[17]. Subsequently, we proposed two novel risk scores and seven machine learning-based models (random survival forest, Ada boost classifier, Gaussian naïve Bayes, light gradient boosting machine, random forest classifier, gradient boosting classifier and decision tree classifier)[18]. Of these, the best performing model for the whole cohort was based on RSF, whereas for the patients who have intermediate risk levels, Gradient boosting classifier achieved the best performance in terms of AUC. Consequently, we proposed PowerAI-Brugada, a clinical tool that provide rapid risk stratification based on our research findings. Another team from Japan developed a model instead based on convolutional neural network (CNN), with a weighted-average precision of 0.79, a recall of 0.73, and an F1 score of 0.75.

For acquired LQTS, deep learning analysis of ECG using CNN was able to identify drug-induced arrhythmias and facilitate its diagnosis[19]. Our team developed a RSF-NMF based model using cancer diagnosis, serum potassium and calcium levels combined with ECG features to predict all-cause mortality[20]. For congenital LQTS, our team was the first to conduct the largest territory-wide analysis of the epidemiology, risk factors, genetics and outcomes of Chinese LQTS patients[21] allowing us to develop predictive models using

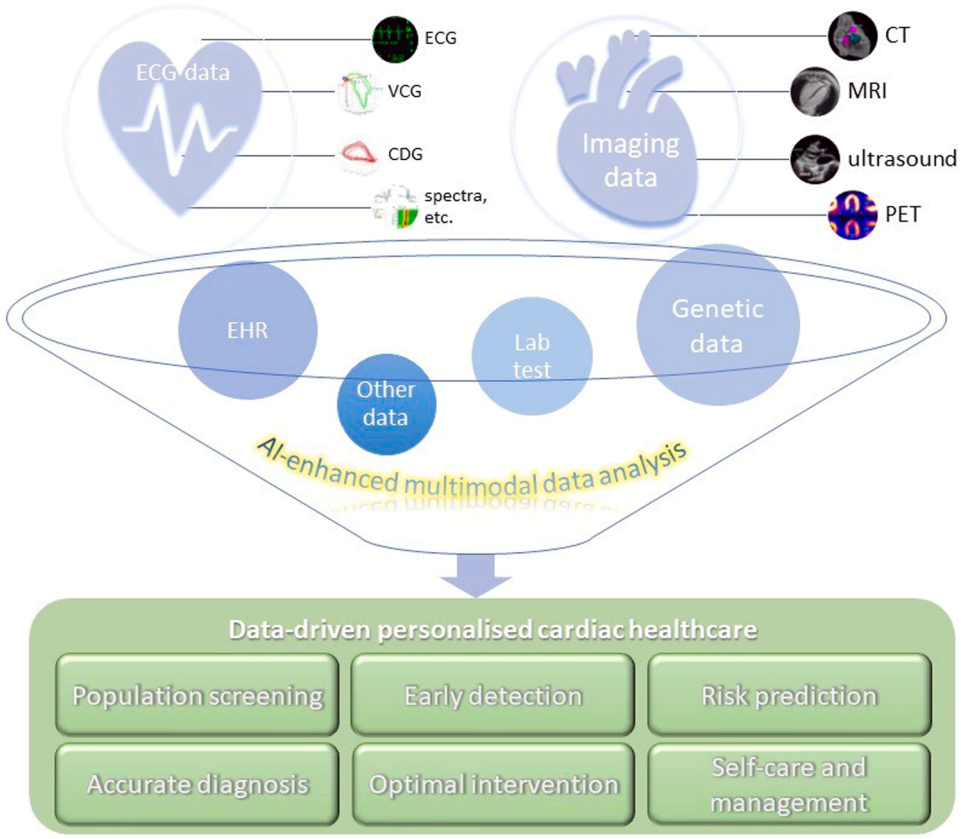

Fig. 5. Approach for model development: routinely collected electronic health records containing multi-modality data were used to develop high performing models. Important data fields include demographic details, disease coding, laboratory test results, medications history, hospital and clinic attendances, genetic data, electrocardiographic, echocardiographic and other imaging data.

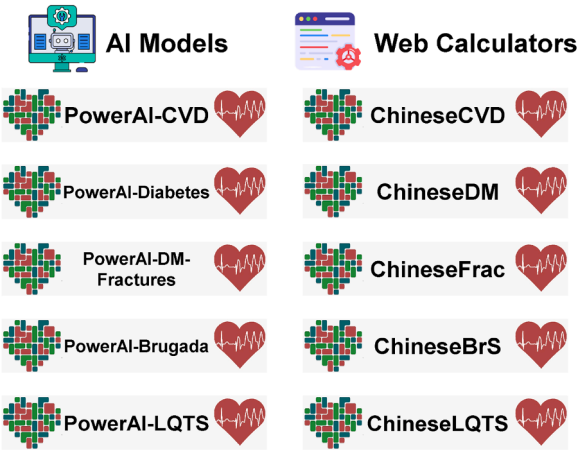

Fig. 6. Summary diagram of AI models and corresponding simpler, web-based calculators developed by our team.

RSF, leading to improvement in precision from 0.69 to 0.80, recall from 0.68 to 0.79, AUC from 0.68 to 0.77 and c-statistic from 0.67 to 0.79 compared to the baseline Cox model[22]. CPVT is the rarest ion channelopathies both globally and in Chinese[23]. From our territory-wide analysis in Hong Kong, we were only able to identify 16 patients[24] which were not sufficient for us to develop a predictive model[25]. Our subsequent systematic review of CPVT cases from China identified a total of 58 cases from 15 case reports or series[26]. Together it is anticipated that AI will be increasingly common and accessible to clinicians for the detection, risk stratification and management of patients with inherited arrhythmic syndromes[27] leading to personalised care[28].

Upcoming and future research

The benefit of our approach is that only routinely collected data are required for developing highly accurate and high-performance models using a multimodality approach (Fig. 5). For cardiovascular diseases, we have already incorporated electrocardiographic and echocardiographic variables to enhance risk prediction.[29,30] Our team is constantly improving our existing models by exploring non-traditional risk factors from the eHRs. For example, we are incorporating socioeconomic as well as functional assessment data from different members of the multidisciplinary team members, including nurses, physiotherapists and occupational therapists. We are also developing new models for different diseases and outcomes. A summary of our current and upcoming AI-driven and simpler web-based models is depicted in Fig. 6.

Concluding Remarks

AI-driven models outperform traditional models in terms of sensitivity, specificity, accuracy, area under the receiver operating characteristic and precision-recall curve, and F1 score. Web and/or mobile versions of the risk models allow clinicians to risk stratify patients quickly in clinical settings, thereby enabling clinical decision-making. Efforts are required to identify the best ways of implementing AI algorithms on the web and mobile apps.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Wu D, Nam R, Leung KSK, et al. Population-based clinical studies using routinely collected data in Hong Kong, China: a systematic review of trends and established local practices. *Cardiovasc Innov Appl*. 2023.
2. Li CK, Xu Z, Ho J, et al. Association of NPAC score with survival after acute myocardial infarction. *Atherosclerosis*. 2020;301:30–36.
3. Li L, Chou OHI, Lu L, et al. PowerAI-CVD - the first Chinese-specific, validated artificial intelligence-powered in-silico predictive model for cardiovascular disease. *medRxiv*. 2023;2023. https://doi.org/10.1016/j.cpcardiol.2023.102168.
4. Yang X, Li J, Hu D, et al. Predicting the 10-year risks of atherosclerotic cardiovascular disease in Chinese population: the China-PAR project (prediction for ASCVD risk in China). *Circulation*. 2016;134:1430–1440.
5. Harada A, Ueshima H, Kinoshita Y, et al. Absolute risk score for stroke, myocardial infarction, and all cardiovascular disease: Japan Arteriosclerosis Longitudinal Study. *Hypertens Res*. 2019;42:567–579.
6. Gosak L, Martinovic K, Lorber M, Stiglic G. Artificial intelligence based prediction models for individuals at risk of multiple diabetic complications: a systematic review of the literature. *J Nurs Manag*. 2022;30:3765–3776.
7. Shi R, Niu Z, Wu B, et al. Nomogram for the risk of diabetic nephropathy or diabetic retinopathy among patients with type 2 diabetes mellitus based on questionnaire and biochemical indicators: a cross-sectional study. *Diabetes Metab Syndr Obes*. 2020;13:1215–1229.
8. Liu S, Zhang R, Shang X, Li W. Analysis for warning factors of type 2 diabetes mellitus complications with Markov blanket based on a Bayesian network model. *Comput Methods Progr Biomed*. 2020;188, 105302.
9. Wang H, Xu Y, Chen Q, Wang X. Diagnosis of complications of type 2 diabetes based on weighted multi-label small sphere and large margin machine. *Appl Intell*. 2021;51:223–236.
10. Lee S, Zhou J, Wong WT, et al. Glycemic and lipid variability for predicting complications and mortality in diabetes mellitus using machine learning. *BMC Endocr Disord*. 2021;21:94.
11. Fan Y, Long E, Cai L, Cao Q, Wu X, Tong R. Machine learning approaches to predict risks of diabetic complications and poor glycemic control in nonadherent type 2 diabetes. *Front Pharmacol*. 2021;12, 665951.
12. Lee S, Zhou J, Leung KSK, et al. Development of a predictive risk model for all-cause mortality in patients with diabetes in Hong Kong. *BMJ Open Diabetes Res Care*. 2021;9.
13. Cho BH, Yu H, Kim K-W, Kim TH, Kim IY, Kim SI. Application of irregular and unbalanced data to predict diabetic nephropathy using visualization and feature selection methods. *Artif Intell Med*. 2008;42:37–53.
14. Chung CT, Lee S, King E, et al. Clinical significance, challenges and limitations in using artificial intelligence for electrocardiography-based diagnosis. *Int J Arrhythmia*. 2022;23:24.
15. Asatryan B, Bleijendaal H, Wilde AAM. Toward advanced diagnosis and management of inherited arrhythmia syndromes: harnessing the capabilities of artificial intelligence and machine learning. *Heart Rhythm*. 2023;20:1399–1407.
16. Tse G, Zhou J, Lee S, et al. Incorporating latent variables using nonnegative matrix factorization improves risk stratification in Brugada syndrome. *J Am Heart Assoc*. 2020;9, e012714.
17. Lee S, Zhou J, Li KHC, et al. Territory-wide cohort study of Brugada syndrome in Hong Kong: predictors of long-term outcomes using random survival forests and non-negative matrix factorization. *Open Heart*. 2021;8, e001505.
18. Lee S, Zhou J, Chung CT, et al. Comparing the performance of published risk scores in Brugada syndrome: a multi-center cohort study. *Curr Probl Cardiol*. 2022;47, 101381.
19. Prifti E, Fall A, Davogustto G, et al. Deep learning analysis of electrocardiogram for risk prediction of drug-induced arrhythmias and diagnosis of long QT syndrome. *Eur Heart J*. 2021;42:3948–3961.
20. Chen C, Zhou J, Yu H, et al. Identification of important risk factors for all-cause mortality of acquired long QT syndrome patients using random survival forests and non-negative matrix factorization. *Heart Rhythm*. 2021;18:426–433.
21. Lee S, Zhou J, Jeevaratnam K, et al. Paediatric/young versus adult patients with long QT syndrome. *Open Heart*. 2021;8.
22. Tse G, Lee S, Zhou J, et al. Territory-wide chinese cohort of long QT syndrome: random survival forest and cox analyses. *Front Cardiovasc Med*. 2021;8, 608592.
23. Lee S, Zhou J, Jeevaratnam K, et al. Paediatric/young versus adult patients with congenital long QT syndrome or catecholaminergic polymorphic ventricular tachycardia. *Eur Heart J*. 2021;42. ehab724.1870.
24. Lee S, Zhou J, Jeevaratnam K, et al. Arrhythmic Outcomes in Catecholaminergic Polymorphic Ventricular Tachycardia. medRxiv. 2021:2021.01.04.21249214.
25. Chung CT, Lee S, Zhou J, et al. Clinical characteristics, genetic basis and healthcare resource utilisation and costs in patients with catecholaminergic polymorphic ventricular tachycardia: a retrospective cohort study. *RCM*. 2022:23.
26. Leung J, Lee S, Zhou J, et al. Clinical characteristics, genetic findings and arrhythmic outcomes of patients with catecholaminergic polymorphic ventricular tachycardia from china: a systematic review. *Life*. 2022:12.

27. Leung KSK, Huang H, Chung CT, et al. Historical perspective and recent progress in cardiac ion channelopathies research and clinical practice in Hong Kong. *Int J Arrhythmia*. 2023;24:9.
28. Lee S, Mok NS, Tse G. Precision medicine for cardiac ion channelopathies in Hong Kong: from case reports to identification of novel genetic variants and development of risk prediction tools using population-based datasets. *J Hong Kong Coll Cardiol*. 2023:30.
29. Tse G, Zhou J, Lee S, et al. Multi-parametric system for risk stratification in mitral regurgitation: a multi-task Gaussian prediction approach. *Eur J Clin Investig*. 2020;50:e13321.
30. Tse G, Zhou J, Woo SWD, et al. Multi-modality machine learning approach for risk stratification in heart failure with left ventricular ejection fraction </= 45. *ESC Heart Fail*. 2020;7:3716–3725.
31. Nakamura T, Aiba T, Shimizu W, Furukawa T, Sasano T. Prediction of the presence of ventricular fibrillation from a Brugada electrocardiogram using artificial intelligence. *Circ J*. 2023;87:1007–1014.