Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

An explainable machine learning clinical decision support system for tailored blood pressure care in adults: integrating arterial stiffness to mitigate overtreatment risks

Xinyue Zhang
Wuhan Union Hospital
Chengyun Liu
Wuhan Union Hospital
Xinlin Chen
X&Y Solutions Inc
zuyun Liu
Second Affiliated Hospital of Zhejiang University
Xueke Guang
Wuhan Union Hospital
Guangyu Gao
Wuhan Union Hospital
Haohui Fan
Wuhan Union Hospital
Hao Zhang
Wuhan Union Hospital
Quan Zhou
Wuhan Union Hospital
Xinqi Diao
Wuhan Union Hospital
Weilin Lu
weilinlu233@163.com

Wuhan Union Hospital

Research Article

Keywords: Hypertension, Machine learning, Clinical decision support system, Pulse wave velocity, Vascular aging, Arterial stiffness, Individualized treatment, Overtreatment, Shared decision-making

Posted Date: November 5th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11078321/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

Background

Hypertension is a leading modifiable risk factor for cardiovascular disease, yet the optimal systolic blood pressure (SBP) target for an individual adult remains uncertain: fixed, aggressive targets can cause cerebral hypoperfusion, orthostatic hypotension, falls and cognitive harm, whereas the optimal target varies with biological vascular aging. Explainable machine learning could tailor blood-pressure care by integrating a marker of vascular aging, but such a clinical decision support system has not been evaluated.

Methods

Using the Framingham Heart Study Offspring and Third Generation cohorts (baseline 1998–2011), we developed and internally validated an explainable machine learning clinical decision support system that predicts the SBP target associated with the lowest risk of major adverse cardiovascular events (MACE). Eight algorithms were compared; features were selected with the variance inflation factor and least absolute shrinkage and selection operator (LASSO) regression; the best model was interpreted with SHapley Additive exPlanations (SHAP) and evaluated by discrimination, calibration and decision curve analysis.

Results

After exclusions, 3912 participants were in the development cohort and 1658 in the internal validation cohort. LASSO selected eight predictors including carotid-femoral pulse wave velocity (cf-PWV), a marker of vascular aging. Random forest performed best (development area under the receiver operating characteristic curve [AUC] 0.74; validation AUC 0.73). SHAP identified cf-PWV as the dominant feature, with a threshold effect near 9.2 m/s above which the recommended target was relaxed. Decision curve analysis showed net benefit across a broad range of threshold probabilities.

Conclusions

Integrating cf-PWV into an explainable machine learning framework supported tailored SBP targets for adults with clinically useful performance, offering an objective, vascular-aging-based approach to mitigate overtreatment risks. The web-based calculator translates the model into a shared-decision tool that keeps clinicians in the loop.

Background

Hypertension is one of the most prevalent chronic conditions and a leading modifiable risk factor for cardiovascular disease, and its prevalence rises steeply with age [1, 2]. It rarely occurs alone: many adults with hypertension also live with multimorbidity [3]. Autonomic dysfunction and orthostatic hypotension are common in this population, and adults with orthostatic hypotension are at increased risk of falls [4]. Although intensive blood-pressure lowering reduces cardiovascular events on average [5, 6], in older and frail adults it can also precipitate cerebral hypoperfusion, symptomatic orthostatic dizziness with falls and fractures, and possible cognitive harm [7]. The optimal SBP target for an individual adult therefore remains uncertain, and the J-curve phenomenon cautions against uniform, aggressive targets [8].

Chronological age is an imperfect proxy for biological risk. With advancing age, cardiovascular risk is more closely tied to vascular aging, the structural and functional deterioration of the arterial tree, than to age itself [9]. Carotid-femoral pulse wave velocity (cf-PWV) is the reference-standard measure of arterial stiffness and a widely accepted phenotypic marker of vascular aging [10], and it independently predicts cardiovascular events beyond conventional risk factors [11]. Although arterial stiffness increases with age, its association with blood pressure and cardiovascular risk varies across individuals [12]. Machine learning can model this nonlinear relationship [13], and explainable methods such as SHapley Additive exPlanations (SHAP) make the resulting recommendations transparent [14]. Integrating a marker of biological aging into a data-driven model therefore offers a more objective basis for tailoring blood-pressure care than judgments based on chronological age alone.

Using data from the Framingham Heart Study (FHS) [15], we aimed to develop and validate an explainable machine learning clinical decision support system that integrates cf-PWV and clinical features to tailor SBP targets for adults, to compare eight algorithms, and to interpret the best model with SHAP. We hypothesized that cf-PWV would show a threshold effect above which the recommended target is relaxed, thereby mitigating the risk of overtreatment.

Methods

This retrospective cohort study used the Framingham Heart Study (FHS) Offspring and Third Generation cohorts (baseline 1998–2011) and was reported per the TRIPOD statement [16]. We included participants aged ≥ 18 years with cf-PWV measured at baseline, complete blood pressure and treatment information, and complete follow-up, and excluded those with established cardiovascular disease, missing key covariates, poor-quality cf-PWV (< 4 or > 25 m/s), pregnancy, or severe hepatic/renal impairment; the primary outcome was major adverse cardiovascular events (MACE; first nonfatal myocardial infarction, nonfatal stroke, or cardiovascular death). Candidate predictors included demographics, lifestyle, medical history, anthropometrics, laboratory measures, medications and cf-PWV measured with the Complior SP device [17]. Missing values (< 20%) were imputed by multiple imputation using chained equations [18], continuous variables were standardized, and the dataset was split 7:3 into development (n = 3912) and internal validation (n = 1658) cohorts. Multicollinearity was assessed with the variance inflation factor (VIF) [19], and least absolute shrinkage and selection operator (LASSO) regression [20] selected a sparse set of predictors. Eight algorithms were compared: logistic regression, support vector machine, random forest [13], decision tree, neural network, XGBoost [21], naive Bayes and k-nearest neighbours. Discrimination was assessed with the area under the receiver operating characteristic curve (AUC) and the area under the precision-recall curve (PRAUC), together with accuracy, sensitivity and specificity, and clinical utility was assessed with decision curve analysis (DCA) [22]; the best model was interpreted with SHAP [14]. Analyses were performed in R version 4.3.1 [23], and a two-sided $P < 0.05$ was considered significant. The overall study design is summarized in Fig. 1.

Results

Participants and baseline characteristics

The development cohort had a mean age of 58.2 ± 9.5 years (52.4% men) and mean cf-PWV of 8.7 ± 2.1 m/s; 641 MACE events occurred (16.4%) over a median follow-up of 12.5 years. The validation cohort had a mean cf-PWV of 9.1 ± 2.4 m/s and a MACE incidence of 17.1% (Table 1).

Table 1
Baseline characteristics of the development and validation cohorts

Characteristic	No MACE (n = 3271)	MACE (n = 641)	P	No MACE (n = 1375)	MACE (n = 283)	P
Age, years, mean ± SD	58.3 ± 10.2	67.5 ± 9.8	< 0.01	59.1 ± 10.5	68.2 ± 9.6	< 0.01
Male sex, n (%)	1647 (51.20)	403 (62.87)	0.08	1020 (74.19)	165 (58.23)	0.03
Diabetes, n (%)	1080 (27.61)	149 (23.33)	0.44	355 (25.81)	104 (36.71)	0.14
Current smoking, n (%)	808 (24.7)	234 (36.5)	< 0.01	349 (25.4)	106 (37.5)	0.34
Alcohol use, n (%)	782 (23.91)	75 (11.67)	0.01	521 (37.90)	68 (24.05)	0.06
Prior stroke, n (%)	290 (8.75)	85 (13.33)	0.22	211 (15.32)	36 (12.66)	0.75
Waist circumference, cm, mean ± SD	81.6 ± 9.4	89.3 ± 10.1	0.65	76.1 ± 9.6	89.8 ± 10.3	0.51
BMI, kg/m2, mean ± SD	22.13 ± 5.99	26.35 ± 8.50	0.45	22.85 ± 4.97	25.60 ± 6.79	0.05
cf-PWV, m/s, mean ± SD	8.25 ± 1.23	13.24 ± 1.26	0.95	8.24 ± 1.25	12.43 ± 1.08	0.26
LDL-c, mmol/L, mean ± SD	2.78 ± 0.97	3.24 ± 0.88	0.34	2.31 ± 0.89	3.13 ± 0.65	0.51
HDL-c, mmol/L, mean ± SD	1.21 ± 0.34	1.02 ± 0.37	0.13	1.25 ± 0.22	1.05 ± 0.37	0.24
TC, mmol/L, mean ± SD	4.61 ± 1.04	5.12 ± 1.23	0.27	4.78 ± 1.37	5.24 ± 1.29	0.95
TG, mmol/L, mean ± SD	1.61 ± 0.61	2.15 ± 1.36	0.21	1.74 ± 0.91	2.22 ± 1.47	0.42
Albumin, g/L, mean ± SD	34.6 ± 2.09	35.1 ± 3.2	0.04	34.7 ± 3.1	35.2 ± 2.2	0.03
Total protein, g/L, mean ± SD	65.32 ± 5.92	63.79 ± 4.38	0.34	64.27 ± 4.87	65.17 ± 3.82	0.66

Left three columns, development cohort (n = 3912); right three columns, internal validation cohort (n = 1658). MACE, major adverse cardiovascular events; SD, standard deviation; BMI, body mass index; cf-PWV, carotid-femoral pulse wave velocity; LDL-c, low-density lipoprotein cholesterol; HDL-c, high-density lipoprotein cholesterol; TC, total cholesterol; TG, triglycerides.

Feature selection and model performance

After collinearity filtering, LASSO selected eight predictors: cf-PWV, age, pulse pressure, diabetes, antihypertensive use, total cholesterol, HDL-c and estimated glomerular filtration rate (eGFR). Random forest showed the best overall performance (development AUC 0.74; validation AUC 0.73) (Table 2, Fig. 2).

Table 2
Performance of the eight machine learning models

Model	AUC (dev)	PRAUC (dev)	Accuracy (dev)	Sensitivity (dev)	Specificity (dev)	AUC (val)	PRAUC (val)	Accuracy (val)	Sensitivity (val)	Specificity (val)
Logistic regression	0.69	0.49	0.71	0.17	0.93	0.70	0.49	0.71	0.09	0.93
Support vector machine	0.69	0.51	0.73	0.46	0.97	0.71	0.52	0.73	0.43	0.96
Random forest	0.74	0.58	0.75	0.78	0.92	0.73	0.58	0.77	0.80	0.92
Decision tree	0.64	0.45	0.72	0.39	0.88	0.62	0.41	0.70	0.80	0.85
Neural network	0.53	0.31	0.69	0.67	0.91	0.52	0.29	0.70	0.54	0.98
XGBoost	0.67	0.47	0.68	0.56	0.77	0.63	0.43	0.68	0.67	0.80
Naive Bayes	0.70	0.48	0.71	0.36	0.91	0.69	0.49	0.72	0.33	0.92
K-nearest neighbours	0.68	0.50	0.69	0.56	0.82	0.68	0.48	0.70	0.67	0.83

dev, development cohort; val, internal validation cohort. AUC, area under the receiver operating characteristic curve; PRAUC, area under the precision-recall curve.

Model interpretation and clinical utility

SHAP identified cf-PWV as the dominant feature, with a threshold effect near 9.2 m/s above which the recommended target was relaxed (Fig. 3). Decision curve analysis showed net benefit across a broad range of threshold probabilities (Fig. 4). Compared with the Framingham risk score variables, the model using the top three SHAP variables (cf-PWV, age and pulse pressure) achieved the highest AUC (0.73) (Table 3).

Table 3
Comparison of random forest models with different feature sets

Model	Variables	AUC	PRAUC	Accuracy	DCA net-benefit threshold probability
Model 1	10 variables	0.72	0.57	0.75	0.33–0.57
Model 2	5 variables	0.70	0.55	0.74	0.32–0.66
Model 3	3 variables	0.73	0.54	0.74	0.29–0.74
Model 4	Framingham score	0.54	0.31	0.71	0.00–0.00

Model 1: cf-PWV, age, pulse pressure, TC, HDL-c, BMI, eGFR, diabetes, sex and alcohol use. Model 2: cf-PWV, age, pulse pressure, TC and HDL-c. Model 3: cf-PWV, age and pulse pressure. Model 4: Framingham risk score variables. AUC, area under the receiver operating characteristic curve; PRAUC, area under the precision-recall curve; DCA, decision curve analysis.

Web-based decision-support tool

An interactive web-based calculator was developed so that clinicians and caregivers can enter basic information and cf-PWV to obtain a recommended individualized SBP target with a confidence interval and a visual explanation of the recommendation (Fig. 5).

Discussion

We developed and internally validated an explainable machine learning clinical decision support system that integrates cf-PWV, a marker of vascular aging, to tailor SBP targets for adults. Random forest performed best (AUC 0.74 and 0.73), and cf-PWV showed a threshold effect near 9.2 m/s above which the recommended target was relaxed, providing a data-driven account of the J-curve and a mechanism to mitigate overtreatment risk.

Vascular aging, tailored targets and model performance

Random forest is well suited to structured tabular data because it captures nonlinear interactions without prespecified functional forms [24]. The leading predictors have clear pathophysiological meaning: cf-PWV reflects arterial remodeling and vascular fibrosis, and age and pulse pressure reflect vascular aging and early wave reflection [25], which makes standardized cf-PWV measurement central to reliable prediction [26]. Because cf-PWV captures biological rather than chronological aging, the model can distinguish adults for whom a conventional low target may be excessive from those for whom it remains appropriate.

Shared decision-making in blood pressure care

A key aim of the system is to augment rather than replace clinical judgment [27]. The web-based calculator presents the recommended SBP target together with a visual explanation of each feature's contribution, so that clinicians, nurses, patients and families can engage in shared decision-making about whether a target should be relaxed or intensified [28]. Making the reasoning transparent can reduce adults' concerns about medication adjustment and thereby improve adherence to the agreed care plan.

Ethics, equity and human-in-the-loop oversight

The FHS cohort is predominantly White and was assembled in a research setting, so deployment in diverse community clinical settings requires explicit monitoring for algorithmic bias, because models trained on non-representative data can inherit and even amplify disparities [29]. Ethical and governance frameworks for health AI require such oversight [30]. We therefore emphasize a human-in-the-loop design: the tool offers a recommendation and an explanation but leaves the final decision to clinicians and patients, so that subjective comfort, symptoms such as dizziness, and individual preferences are not displaced by automated outputs [27].

Care workflow and accessibility

For the system to reach routine clinical care, cf-PWV measurement must move from specialized laboratories into community clinics, residential care settings and home monitoring [31]. Portable devices and cuff-based surrogate estimates, together with remote blood-pressure monitoring [32], could lower the technical barrier and extend tailored blood-pressure care into everyday chronic-care workflows [33].

Limitations

The FHS cohort is predominantly White and includes adults younger than 60 years, so external validation in more diverse populations is needed; reference values for arterial stiffness also differ across populations [34, 35]. The model is static and based on a single baseline assessment; integrating longitudinal PWV, ambulatory blood pressure and wearable data could support dynamic adjustment of the target over time [32, 36]. Prospective validation is required before deployment [37].

Conclusions

We developed and internally validated an explainable machine learning clinical decision support system that integrates cf-PWV, a marker of vascular aging, to tailor SBP targets for adults. Random forest outperformed the other seven algorithms and the Framingham risk score variables (AUC 0.74 and 0.73).

SHAP revealed a threshold relationship between arterial stiffness and the recommended target, providing a data-driven mechanism to mitigate overtreatment risks in multimorbid patients. The web-based calculator translates the model into a shared decision-making tool; future work should validate it prospectively in diverse populations, integrate wearable and home monitoring, and maintain human-in-the-loop oversight so that AI supports rather than replaces clinical judgment.

Declarations

Ethics approval and consent to participate

This study was a secondary analysis of de-identified data from the Framingham Heart Study (FHS) Offspring and Third Generation cohorts, obtained through dbGaP and BioLINCC. The study did not involve direct recruitment or contact with human participants, and was conducted in accordance with the Declaration of Helsinki. Access to and use of the data were conducted in accordance with the requirements and policies of the respective data repositories. Because the analysis used de-identified secondary data, informed consent was not required for this study in accordance with the applicable data-use and ethics policies. Clinical trial number: not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The FHS datasets are available from the National Heart, Lung, and Blood Institute via dbGaP (https://www.ncbi.nlm.nih.gov/gap/) and BioLINCC (https://biolincc.nhlbi.nih.gov/) upon request and approval. Analysis code is available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

This study received no specific funding.

Authors' contributions

XZ and WL conceived and designed the study. XZ, CL, XC, XG, GG, HF, HZ, QZ, XD and ZL contributed to data acquisition, analysis and interpretation; XC performed the statistical analysis. XZ drafted the manuscript, and WL critically revised it for important intellectual content. All authors read and approved the final manuscript.

Acknowledgements

The authors thank the Framingham Heart Study participants and investigators, and the National Heart, Lung, and Blood Institute, for making the data publicly available through dbGaP and BioLINCC.

Authors' information

Not applicable.

References

1. World Health Organization. Decade of healthy ageing: baseline report. Geneva: World Health Organization; 2021.
2. World Health Organization. Global report on hypertension: the race to a healthier world. Geneva: World Health Organization; 2023.
3. Barnett K, Mercer SW, Norbury M, et al. Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study. Lancet. 2012;380(9836):37-43.
4. Gangavati A, Hajjar I, Quach L, et al. Hypertension, orthostatic hypotension, and the risk of falls in a community-dwelling elderly population: the maintenance of balance, independent living, intellect, and zest in the elderly of Boston study. J Am Geriatr Soc. 2011;59(3):383-9.
5. SPRINT Research Group, Wright JT Jr, Williamson JD, et al. A randomized trial of intensive versus standard blood-pressure control. N Engl J Med. 2015;373(22):2103-16.

6. STEP Study Group, Zhang W, Zhang S, et al. Trial of intensive versus standard blood-pressure control in older patients with hypertension. N Engl J Med. 2021;385(14):1268-79.
7. Williamson JD, Pajewski NM, Auchus AP, et al. Effect of intensive vs standard blood pressure control on probable dementia: a randomized clinical trial. JAMA. 2019;321(6):553-61.
8. Messerli FH, Paneni F, Kotovskaia Y, et al. The J-curve in hypertension: a 2023 perspective. J Am Coll Cardiol. 2023;82(6):561-73.
9. Laurent S, Boutouyrie P, Cunha PG, Lacolley P, Nilsson PM. Concept of extremes in vascular aging. Hypertension. 2019;74(2):218-28.
10. Van Bortel LM, Laurent S, Boutouyrie P, et al. Expert consensus document on the measurement of aortic stiffness in daily practice using carotid-femoral pulse wave velocity. J Hypertens. 2012;30(3):445-8.
11. Ben-Shlomo Y, Spears M, Boustred C, et al. Aortic pulse wave velocity improves cardiovascular event prediction: an individual participant meta-analysis of prospective observational data from 17,635 subjects. J Am Coll Cardiol. 2014;63(7):636-46.
12. Heffernan KS, Jae SY, Loprinzi PD. The interaction of age, sex, and blood pressure on arterial stiffness in a nationally representative sample of US adults. Am J Hypertens. 2022;35(4):350-6.
13. Breiman L. Random forests. Mach Learn. 2001;45(1):5-32.
14. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. Adv Neural Inf Process Syst. 2017;30:4765-74.
15. Mahmood SS, Levy D, Vasan RS, et al. The Framingham Heart Study and the epidemiology of cardiovascular disease: a historical perspective. Lancet. 2014;383(9921):999-1008.
16. Collins GS, Reitsma JB, Altman DG, et al. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. Ann Intern Med. 2015;162(1):55-63.
17. Asmar R, Topouchian J, Pannier B, et al. Validation of the Artech Medical Complior SP device for pulse wave velocity (PWV) measurement. J Hypertens. 2005;23(11):2137-42.
18. van Buuren S, Groothuis-Oudshoorn K. mice: multivariate imputation by chained equations in R. J Stat Softw. 2011;45(3):1-67.
19. Kim JH. Multicollinearity and misleading statistical results. Korean J Anesthesiol. 2019;72(6):558-69.
20. Tibshirani R. Regression shrinkage and selection via the lasso. J R Stat Soc Series B Stat Methodol. 1996;58(1):267-88.
21. Chen T, Guestrin C. XGBoost: a scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; 2016. p. 785-94.
22. Vickers AJ, Elkin EB. Decision curve analysis: a novel method for evaluating prediction models. Med Decis Making. 2006;26(6):565-74.
23. R Core Team. R: a language and environment for statistical computing. Vienna: R Foundation for Statistical Computing; 2023.
24. Shwartz-Ziv R, Armon A. Tabular data: deep learning is not all you need. Inf Fusion. 2022;81:84-90.
25. Chirinos JA, Kips JG, Jacobs DR Jr, et al. Arterial wave reflections and incident cardiovascular events and heart failure: MESA (Multi-Ethnic Study of Atherosclerosis). J Am Coll Cardiol. 2012;60(21):2170-7.
26. Laurent S, Cockcroft J, Van Bortel L, et al. Expert consensus document on arterial stiffness: methodological issues and clinical applications. Eur Heart J. 2006;27(21):2588-605.
27. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56.
28. Stiggelbout AM, Pieterse AH, De Haes JCJM. Shared decision making: concepts, evidence, and practice. Patient Educ Couns. 2015;98(10):1172-9.
29. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-53.
30. World Health Organization. Ethics and governance of artificial intelligence for health: WHO guidance. Geneva: World Health Organization; 2021.
31. Coravos A, Khozin S, Mandl KD. Developing and adopting safe and effective digital biomarkers to improve patient outcomes. NPJ Digit Med. 2019;2:14.
32. Kario K. Management of hypertension in the digital era: small wearable monitoring devices for remote blood pressure monitoring. Hypertension. 2020;76(3):640-50.
33. Parati G, Stergiou GS, Bilo G, et al. Home blood pressure monitoring: methodology, clinical relevance and practical application: a 2021 position paper by the Working Group on Blood Pressure Monitoring and Cardiovascular Variability of the European Society of

Hypertension. J Hypertens. 2021;39(9):1742-67.
34. Wang J, Zhang L, Wang F, et al. Prevalence, awareness, treatment, and control of hypertension in China: results from a national survey. Am J Hypertens. 2014;27(11):1355-61.
35. Li Y, Wang JG, Dolan E, et al. Reference values for arterial stiffness in a Chinese population. J Hypertens. 2010;28(10):2086-92.
36. Parati G, Ochoa JE, Lombardi C, et al. Assessment and management of blood-pressure variability. Nat Rev Cardiol. 2013;10(3):143-55.
37. Wallace E, Uthman OA, Trikalinos TA, et al. A framework for the prospective validation of clinical prediction models. BMJ. 2023;381:e073746.

Figures

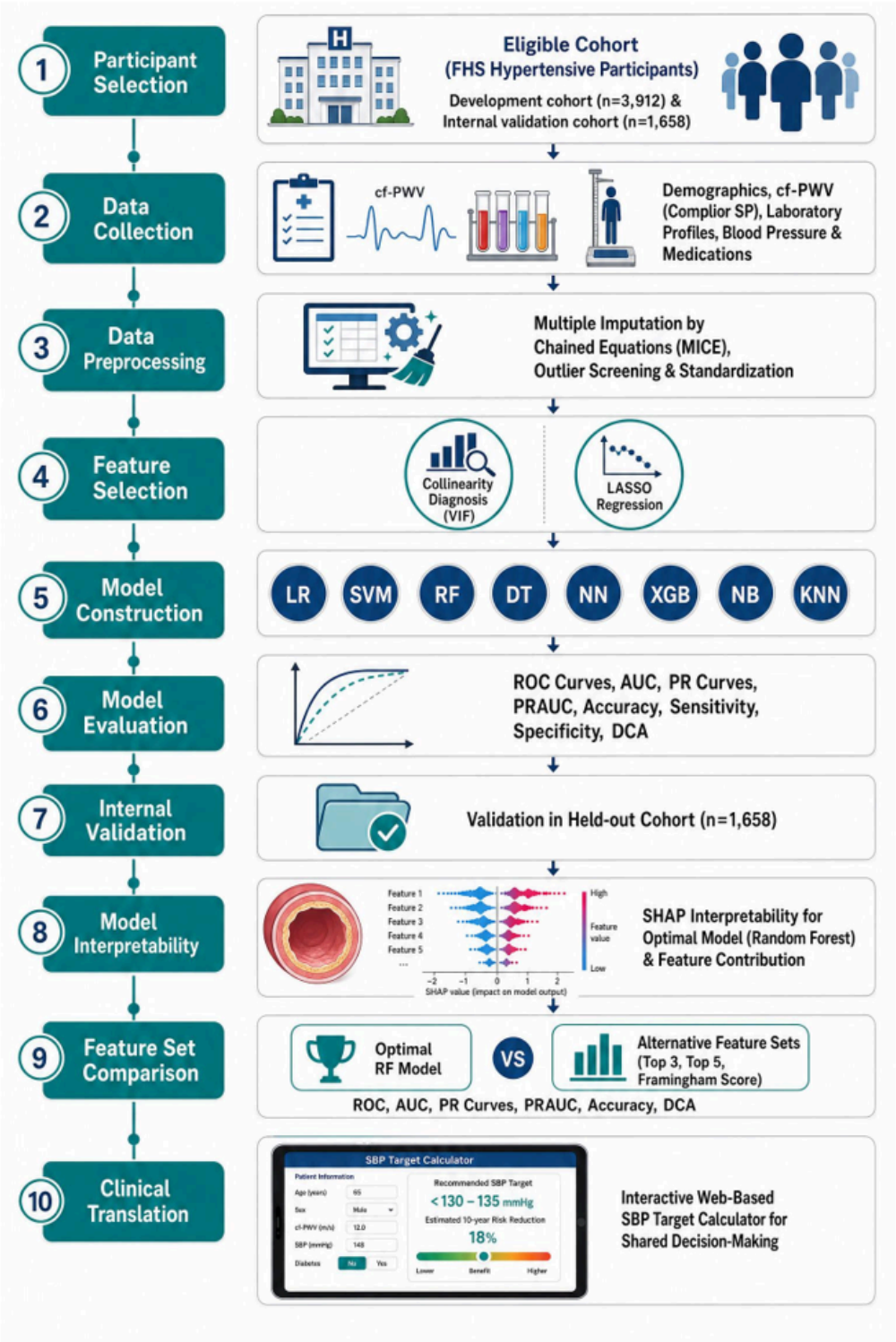


Figure 1

Study design flowchart

Participant selection, data preprocessing, model development, validation and clinical translation.

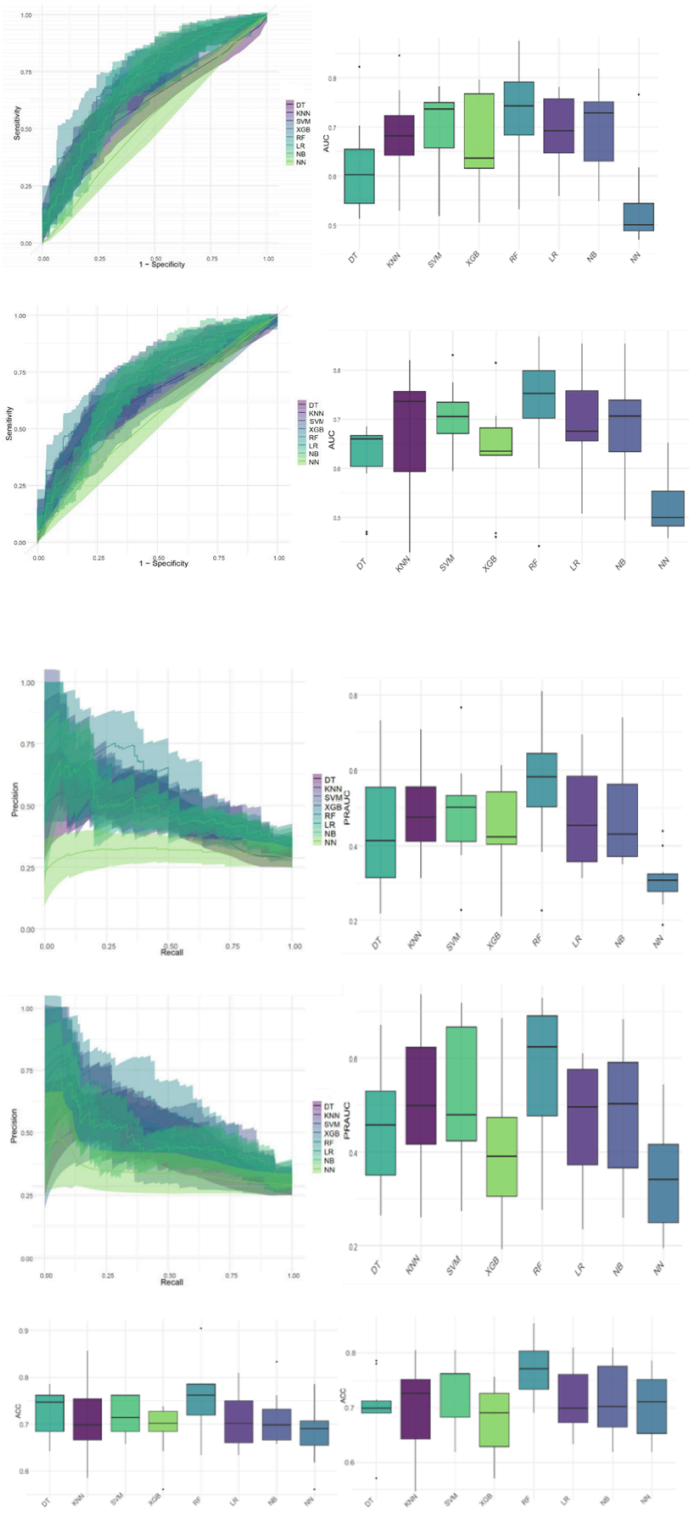


Figure 2

Comparison of eight machine learning algorithms

ROC curves, AUC boxplots, precision-recall curves, PRAUC boxplots and accuracy boxplots in the development and validation cohorts. LR, logistic regression; SVM, support vector machine; RF, random forest; DT, decision tree; NN, neural network; NB, naive Bayes; KNN, k-nearest neighbours.

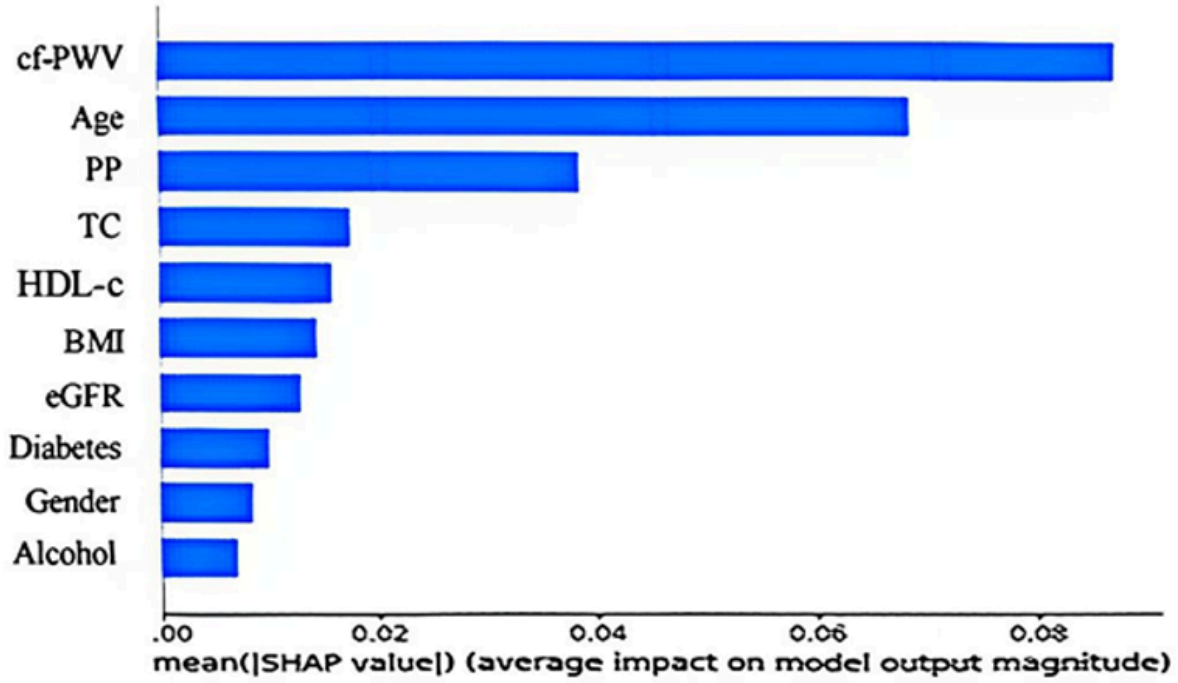


Figure 3

SHAP feature analysis of the random forest model

SHAP values quantify the contribution of each feature to the predicted outcome.

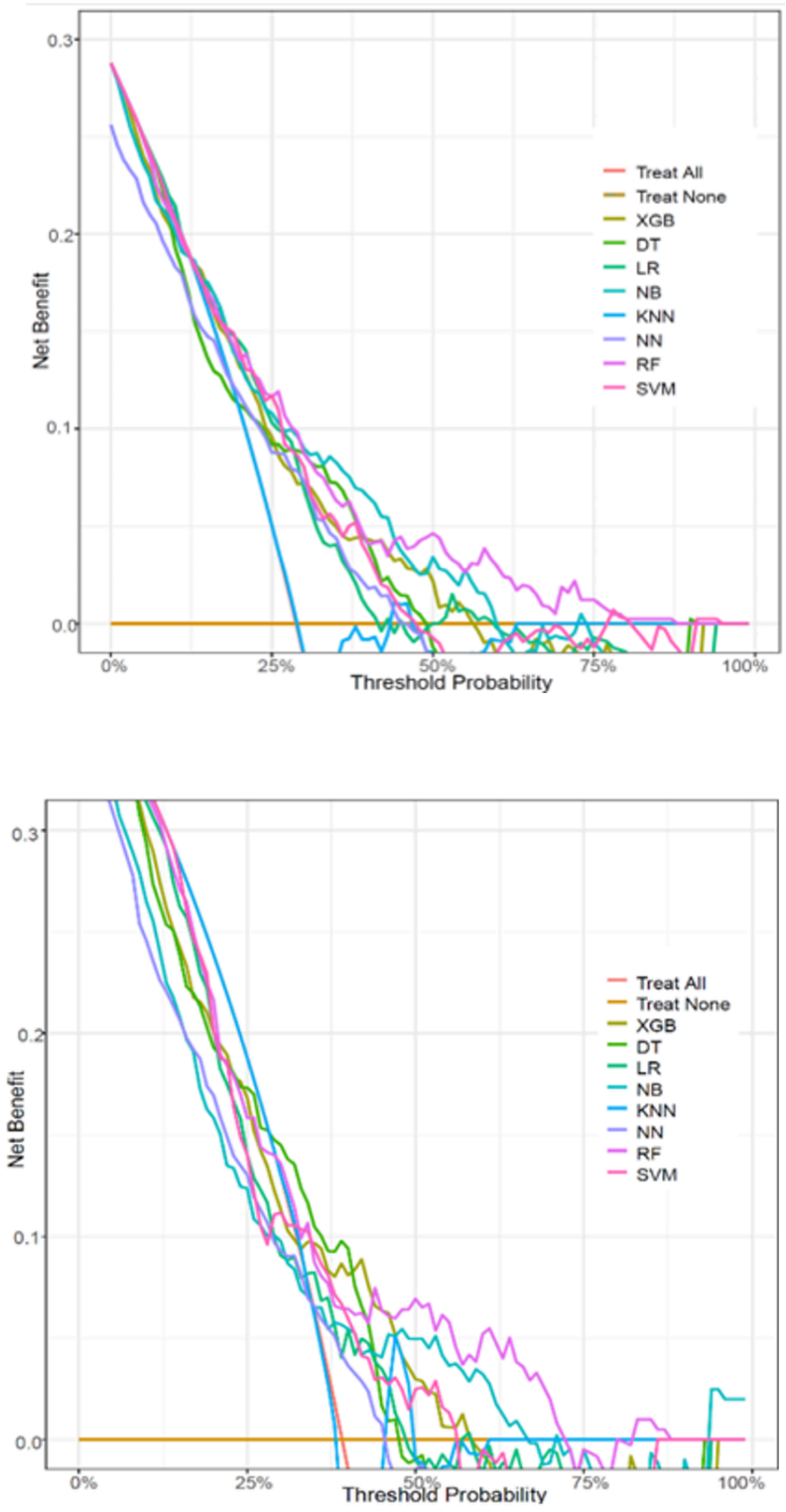


Figure 4

Decision curve analysis in the development and validation cohorts

(a) Development cohort; (b) validation cohort. The dashed lines represent the treat-all and treat-none strategies.

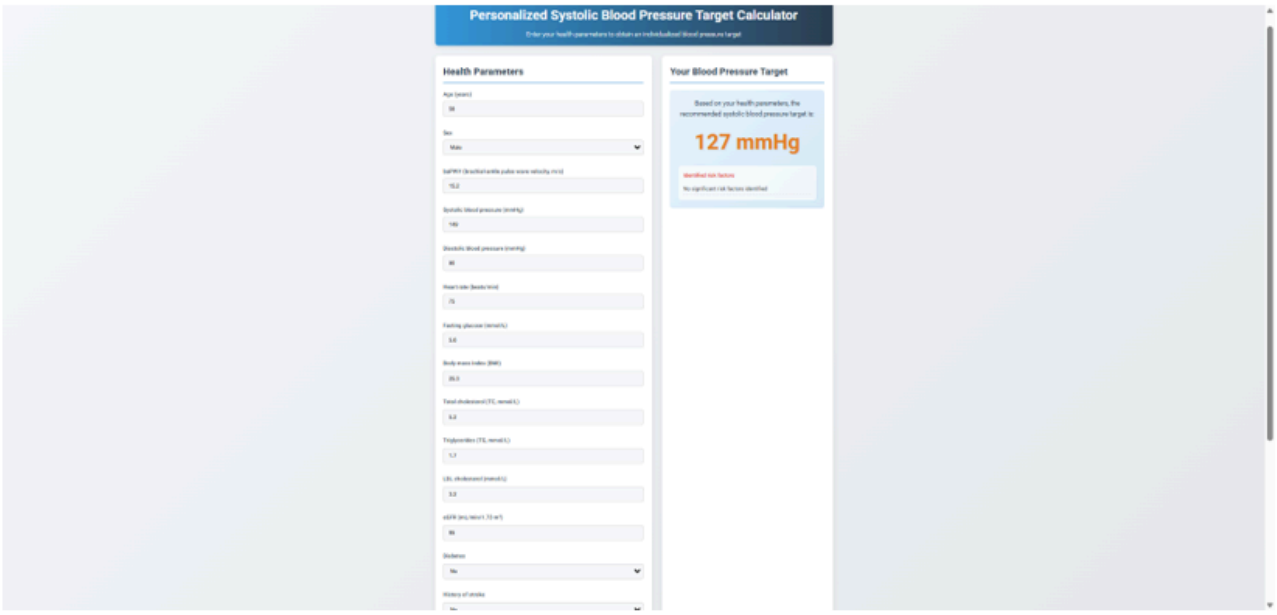


Figure 5

Interactive web-based prediction calculator

The calculator outputs the recommended individualized SBP target and visualizes feature contributions.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- calculatorEN.html