Artificial Intelligence-driven prediction models for early detection and individualized management of morning hypertension

Modelos de predicción basados en inteligencia artificial para la detección temprana y el tratamiento individualizado de la hipertensión matutina

Ashurova Nigora - Doctor of Medical Sciences, Associate Professor of the Department of the Obstetric and Gynecology in Family Medicine, Bukhara state medical institute named after Abu Ali ibn Sino, Bukhara, Uzbekistan; https://orcid.org/0009-0002-8378-1334, E-mail: ashurova.nigora@bsmi.uz
Radjabova Zulola - PhD, Assistant of the Department of Obstetrics and Gynecology-2, Center for the development of professional qualification of medical workers, Tashkent, Republic of Uzbekistan; E-mail: radjabova.z@yandex.ru, https://orcid.org/0009-0008-9408-9312
Boboqulova Sarvara - PhD, Department of the Obstetrics and Gynecology in Family Medicine, Bukhara state medical institute named after Abu Ali ibn Sino, Bukhara, Uzbekistan; https://orcid.org/0000-0003-4473-7277, E-mail: boboqulova.sarvara@bsmi.uz
Badritdinova Matluba - Associate Professor, Bukhara State Medical Institute, Republic of Uzbekistan, https://orcid.org/0000-0002-7814-4106, E-mail: matlubabadritdinova17@gmail.com
Khusenov Olim - Associate Assistant, Bukhara State Medical Institute, Republic of Uzbekistan, https://orcid.org/0000-0003-3300-4289, E-mail: okhusenov1977@gmail.com
Guloyim Avezova - Department of propaedeutics of children's diseases, Tashkent State Medical university, Tashkent, Republic of Uzbekistan; https://orcid.org/0000-0002-2963-3608, guloyimavezova77@gmail.ru
Qushnazarova Ugiljon - Department of Pedagogy and psychology, Urgench state university, Urgench city, Uzbekistan; ogiljon@urdu.uz, https://orcid.org/0009-0001-8767-6921
8) Elmurodov Tulkin - Tashkent State Technical University named after Islam Karimov, Tashkent, Republic of Uzbekistan; tulqinelmurodov1992@gmail.com, **https://orcid.org/0009-0002-4223-4334**;
Received: 05/20/2025 Accepted: 08/19/2025 Published: 09/12/2025 DOI: http://doi.org/10.5281/zenodo.17021118

Abstract

Morning hypertension as an independent risk factor for cardiovascular events requires novel approaches in prediction and specific treatment. In this study, on the basis of cutting-edge deep learning technologies, an early prediction model of this phenomenon was developed. In a prospective cohort of 1,850 patients with essential hypertension, continuous blood pressure monitoring and multimodal physiological, clinical, and behavioral data collection were applied. Results showed that 27.7% of the subjects presented a morning hypertension pattern, which is associated with characteristic hemodynamic abnormalities, including inadequate nocturnal BP dipping and a stark BP surge upon wake time. The optimal LSTM model (AUC=0.92, 87% sensitivity, 89% specificity) could predict subjects at risk as early as a fortnight before the event with 82% accuracy. Feature importance analysis revealed the precedence of sleep parameters and pre-awakening blood pressure, demonstrating the need for updating traditional screening protocols. This system, with persistent good performance on external validation (AUC=0.89), forms the basis of early warning systems and personalized intervention.

Keywords: Morning hypertension, Predictive AI, Deep learning, Personalized intervention

Resumen

La hipertensión matutina, como factor de riesgo independiente de eventos cardiovasculares, requiere enfoques novedosos para su predicción y tratamiento específico. En este estudio, utilizando tecnologías de aprendizaje profundo de vanguardia, se desarrolló un modelo de predicción temprana de este fenómeno. En una cohorte prospectiva de 1850 pacientes con hipertensión esencial, se aplicó la monitorización continua de la presión arterial y la recopilación multimodal de datos fisiológicos, clínicos y conductuales. Los resultados mostraron que el 27,7% de los sujetos presentó un patrón de hipertensión matutina, asociado con anomalías hemodinámicas características, como descensos nocturnos inadecuados de la presión arterial y un aumento brusco de la presión arterial al despertar. El modelo LSTM óptimo (AUC = 0,92, sensibilidad del 87%, especificidad del 89%) permitió predecir el riesgo de los sujetos incluso dos semanas antes del evento con una precisión del 82%. El análisis de importancia de las características reveló la precedencia de los parámetros del sueño y la presión arterial antes del despertar, lo que demuestra la necesidad de actualizar los protocolos de cribado tradicionales. Este sistema, con un buen rendimiento persistente en la validación externa (AUC = 0,89), constituye la base de los sistemas de aler-

ta temprana y la intervención personalizada.

Palabras clave: Hipertensión matutina, IA predictiva, aprendizaje profundo, intervención personalizada

Introducción

Morning hypertension, or a pronounced increase in blood pressure during the initial part of the waking period, represents a severe clinical problem with critical cardiovascular consequences[1]. This distinctive blood pressure pattern is independently associated with increased risk for adverse cardiovascular events such as stroke, heart attack, and heart failure. Early identification and effective management of this condition are key to preventing disabling complications and relieving the burden of cardiovascular disease on healthcare systems[2]. Nevertheless, traditional blood pressure measurement on the basis of sporadic office measurements or poor-quality home samples faces a critical dilemma in detecting the morning hypertension's transient and distinctive pattern. These approaches are frequently not able to reflect reliably blood pressure changes occurring at this vulnerable time interval and potentially lead to underdiagnosis or delayed treatment[3]. Therefore, there is an appreciable disparity in our being able to detect early high-risk subjects and being able to prescribe individualized management measures for maximal control of blood pressure at such crucial periods[4]. This imperative is driven by the imperative to develop and apply more advanced tools for targeted prediction and prevention. The emergence and recent advancements with artificial intelligence and machine learning promise a paradigm shift here[5]. The ability of these technologies to analyze large volumes of complex and heterogeneous data, such as continuous physiological data, lifestyle data, and medical history, holds unprecedented potential to yield reliable, person-specific predictive models[6]. These models could, in theory, not only identify at-risk individuals for morning hypertension prior to complication onset, but also provide entry points into the development of entirely personalized management regimens based upon each patient's unique characteristics. This might lead to revolutionary improvement in clinical outcomes and quality of life for victims[7].

Morning hypertension, as a discrete and isolated entity within the spectrum of blood pressure disturbances, has been the subject of serious inquiry over recent decades[8]. Epidemiological studies have consistently and firmly demonstrated the association between increased blood pressure in the early hours after awakening and the onset of high-level cardiovascular events, such as ischemic and hemorrhagic stroke, myocardial infarction, and acute heart failure[9]. This association has been detected even in patients with normal blood pressure at other times of the day, and it serves to highlight the specific importance of this temporal pattern and the requirement for independent clinical evaluation of it[10]. Even where there is recognition of severe clinical hazard, prompt and precise diagnosis of morning hypertension has always posed practical problems[11]. Conventional monitoring methods, such as a single reading in the clinic or even limited home monitoring for a few days, are generally too insensitive and inaccurate to capture the transient character and temporal specificity of this rise in blood pressure[12].

These methods cannot provide a complete and continuous picture of blood pressure alteration throughout the critical morning period and thus lead to partial diagnosis or detection failure in high-risk groups[13]. Initial endeavors at the development of risk prediction models have largely employed standard statistical modeling and small-scale and static datasets. These had no capability to manage the inherent complexity of dynamic physiological information, synthesize multiple sources of information (e.g., continuous monitoring data, lifestyle variables, drug therapy records, and biomarkers), or take nonlinear interactions of contributing factors into account[14,15]. Therefore, their ability to make proper estimation of individual risk for morning hypertension or its complications, especially on the individual level, remains constrained[16]. These constraints reiterate the need for new analytical paradigms able to detect hidden patterns and complex relationships between heterogeneous and multidimensional sets of data[17]. Recent advances in the field of complex data processing and the emergence of advanced computational architectures have offered new possibilities for bridging these gaps[18].

Study Design and Participant Selection

The current study is a prospective cohort study for developing and cross-validating AI prediction models for morning hypertension. The study population will consist of adults aged ≥18 years with a history of primary hypertension or high cardiovascular risk. Multistage random sampling will be done from participating medical centers within different geographical locations. Inclusion criteria include the ability to be followed up for blood pressure for a specified period of time and informed consent, while exclusion criteria include the development of advanced renal failure, pregnancy, or active malignant diseases. The research protocol was given clearance by the Medical Research Ethics Committee, and strict observance of the Helsinki Principles of Ethics was ensured.

Data acquisition and measurement approaches

Physiological trend data will be assessed using wearable devices with clinically proven sensors that measure continuously and non-invasively systolic and diastolic blood pressure throughout the day. Actively observe for at least seven consecutive days, and focus more on the period from morning until four hours after waking up. In addition, various clinical parameters (e.g., lipid profile, HbA1c, renal function), lifestyle parameters (physical activity, sleep pattern, salt and caffeine intake), medication history and socio-demographic data will be collected using standard questionnaires, electronic medical records and paraclinical tests. All the measuring equipment will be pre-calibrated before distribution and the participants will be given instructions on how to use them.

Development of predictive models

The machine learning and deep learning-based analytical framework is used in the research. In the initial step, extensive preprocessing of data involving missing value handling using sophisticated algorithms like K-Nearest Neighbors (KNN), outlier detection and correction, and feature normalization is conducted. Spatio-temporal feature design including blood pressure oscillation pattern extraction in morning hours, blood pressure rise slope after awakening, and dynamic correlation with other vital signs is on the list. Such significant algorithms used are Random Forests, Support Vector Machine (SVM) with nonlinear kernels, Convolutional Neural Networks (CNN) for time series data analysis, and Long-Span Recurrent Neural Networks (LSTM) for modeling long-term dependencies.

Model Validation and Performance Measurement

Model generalizability is checked using nested cross-validation by dividing the data into independent training, validation, and testing sets. The major performance measures will be Sensitivity, Specificity, Receiver Operating Characteristic Curve (ROC-AUC), Accuracy, and F1 index. In order to describe advanced models (especially black-box models), SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) interpretability techniques are used to reveal key prediction features and their interactions. Stability and robustness of derived models across different population subgroups will be also checked. Statistical analysis is performed using Python software (version 3.11) and specialized libraries Scikit-learn, TensorFlow, and PyTorch.

Table 1: Baseline Characteristics of the Study Cohort

Variable	Total (n=1,850)	Morning Hypertension (n=512)	Non-Morning Hypertension (n=1,338)	p-value
Age (years)	58.3 ± 11.7	63.1 ± 9.8	56.4 ± 11.2	<0.001
Male (%)	54.6	61.3	51.8	0.002
BMI (kg/m²)	28.4 ± 4.1	30.2 ± 3.9	27.8 ± 4.0	<0.001
Diabetes Mellitus (%)	32.7	48.9	26.3	<0.001
Baseline SBP (mmHg)	142.6 ± 14.3	154.2 ± 12.1	138.1 ± 13.2	<0.001

The 1,850 essential hypertension patients included 27.7% with morning hypertension. Baseline group differences were significant, with the morning hypertension subgroup being older (63.1 vs 56.4 years, p<0.001), having higher BMI (30.2 vs 27.8 kg/m², p<0.001), higher prevalence of diabetes (48.9% vs 26.3%, p<0.001), and higher baseline systolic blood pressure (154.2 vs 138.1 mmHg, p<0.001). These findings establish uncomplicated phenotypic differences in the high-risk population.

Table 2: Nocturnal and Morning Blood Pressure Profiles

Parameter	Morning Hypertension Group (n=512)	Control Group (n=1,338)	p-value
Nocturnal SBP dip (%)	6.1 ± 3.2	11.4 ± 4.1	<0.001
Morning SBP surge (mmHg)	28.7 ± 8.3	12.1 ± 5.6	<0.001
Pre-waking SBP (mmHg)	136.4 ± 10.2	122.8 ± 8.7	<0.001
Peak morning SBP (mmHg)	168.3 ± 13.5	134.9 ± 9.8	<0.001

Ambulatory monitoring of blood pressure revealed striking physiological differences between groups. Those with morning hypertension showed profoundly attenuated nocturnal dipping (6.1% vs 11.4%, p<0.001), increased morning surge (28.7 vs 12.1 mmHg, p<0.001), and high pre-waking systolic pressures (136.4 vs 122.8 mmHg, p<0.001). Systolic peak morning pressure rose to clinically concerning levels (168.3 mmHg) in the impacted group, evidence of the hemodynamic severity of this phenotype.

Table 3: Predictive Model Performance Metrics

Algorithm	AUC (95% CI)	Sensitivity	Specificity	F1-Score
LSTM	0.92 (0.89-0.94)	0.87	0.89	0.85
Random Forest	0.88 (0.85-0.91)	0.83	0.85	0.80
XGBoost	0.90 (0.87-0.93)	0.85	0.86	0.82
SVM	0.84 (0.81-0.87)	0.79	0.83	0.76

Deep learning models depicted superior predictive performance on the risk of morning hypertension. LSTM model demonstrated excellent performance (AUC=0.92, 95% CI: 0.89-0.94), much stronger than the usual machine learning techniques. The capacity of recurrent networks to recognize temporal patterns translated into 87% sensitivity and 89% specificity, suggesting excellent discriminative ability for clinical applications.

Table 4: Feature Importance Rankings (SHAP Analysis)

Feature	Mean SHAP Value
Pre-awakening SBP	0.214
Nocturnal SBP slope	0.187
Sleep efficiency (%)	0.162
Cortisol awakening response	0.148
Physical activity (MET-hrs)	0.132
Sodium-to-potassium ratio	0.121

Interpretability analysis revealed strong determinants of the risk of morning hypertension. The strongest determinant was pre-awakening systolic blood pressure (SHAP value=0.214), followed by nocturnal features of blood pressure slope. Notably, sleep efficiency indicators were stronger than traditional risk factors, demonstrating the importance of sleep architecture for the dysregulation of morning blood pressure.

Table 5: Subgroup Performance Analysis

Subgroup	n	LSTM AUC (95% CI)	XGBoost AUC (95% CI)
Diabetic	605	0.89 (0.85-0.92)	0.86 (0.82-0.90)
Age ≥65	742	0.91 (0.88-0.94)	0.88 (0.85-0.91)
CKD Stage 3	319	0.87 (0.83-0.91)	0.84 (0.80-0.88)

Strict validation confirmed model generalizability. Internal-external paradigm validation showed maintained discriminative ability (AUC=0.89 vs 0.92) and calibration (slope=0.97) between geographically distinct populations. The 3-4% external cohort performance decline noted is within expected ranges for clinical prediction models.

Table 6: Impact of Feature Ablation on Model Performance

Removed Feature	Δ AUC	Δ Sensitivity
Temporal BP patterns	-0.21	-0.24
Sleep parameters	-0.15	-0.18
Biochemical markers	-0.09	-0.11
Lifestyle factors	-0.07	-0.08

Systematic feature ablation quantified the relative contribution of data modalities. Removal of temporal blood pressure characteristics caused the most substantial performance decline (ΔAUC=-0.21), confirming their fundamental predictive value. Sleep parameters demonstrated greater importance than biochemical or lifestyle factors, suggesting their indispensable role in accurate risk stratification.

Table 7: Early Detection Capability (Pre-Event Prediction)

Time Window	Precision	Recall	F1-Score
1 week	0.76	0.81	0.78
2 weeks	0.82	0.79	0.80
4 weeks	0.85	0.76	0.80

The model demonstrated clinically meaningful early detection capability, identifying 81% of morning hypertension cases one week before occurrence with 76% precision. Predictive performance peaked at two-week prediction horizons (F1-score=0.80), suggesting optimal lead time for preventive interventions.

Table 8: Validation Cohort Performance Metrics

Metric	Internal Validation	External Validation
AUC	0.92 (0.89-0.94)	0.89 (0.86-0.92)
Sensitivity	0.87	0.83
Specificity	0.89	0.85
Calibration slope	1.02	0.97

Rigorous validation confirmed model generalizability. The internal-external validation paradigm demonstrated preserved discriminative ability (AUC=0.89 vs 0.92) and calibration (slope=0.97) in geographically distinct populations. The observed 3-4% performance attenuation in external cohorts falls within expected ranges for clinical prediction models.

Discussion

The findings of this study are a major step toward the understanding, prediction, and control of morning hypertension in targeted manner. A systematic study of 1,850 patients found that 27.7% of primary hypertensive patients were identified to have morning hypertension criteria. The results not only substantiate the existence of significant physiological and clinical heterogeneity in the population, but also quantify the effectiveness of AI-based approaches. Comparison by group revealed the morning hypertensive group to be older (mean 63.1 vs. 56.4 years, $p<0.001$), more obese with a higher body mass index (30.2 vs. 27.8 kg/m2, $p<0.001$), and had a higher prevalence of diabetes (48.9% vs. 26.3%, $p<0.001$).

The striking hemodynamic difference, specifically the impaired suppression of nocturnal blood pressure (mean nocturnal systolic dip 6.1% vs. 11.4%, $p<0.001$) and the maximal morning rise in blood pressure (mean morning surge 28.7 vs. 12.1 mmHg, $p<0.001$), highlights the dynamic pathophysiology of this condition. The peak morning systolic pressure in the affected group attained alarming levels of 168.3 mmHg, highlighting the hemodynamic severity of this phenotype. Most importantly, there was excellent performance of the predictive models with deep learning. LSTM architecture outperformed other algorithms with an area under the curve of 0.92 (95% confidence interval: 0.89-0.94), sensitivity of 87%, and specificity of 89%. The model performed consistently well even in high-risk populations such as diabetics (AUC=0.89) and elderly (AUC=0.91). The ability to forecast the incidence of morning hypertension with 81% sensitivity and 76% accuracy a week in advance is a valuable intervention window in time.

SHAP feature importance analysis identified pre-awakening systolic blood pressure as having the greatest impact (SHAP value=0.214). To our surprise, sleep variables (SHAP value=0.162) ranked higher than traditional factors such as biochemical markers. Systematic feature deletion confirmed that removal of temporal blood pressure patterns caused the greatest decline in performance (0.21ΔAUC reduction). Model stability across independent groups confirmed generalizability. External validation indicated that the model showed negligible performance reduction (3–4%) while maintaining an AUC=0.89 (95% confidence interval: 0.86–0.92) and calibration slope of 0.97, within the clinical model expected range.

Despite success, the week-long observation window would fail to capture longer-term dynamics. In addition, the moderate loss in performance in renal failure patients (AUC=0.87) indicates population-specific calibration. Still, the predictive power at the individual level constitutes a solid foundation for designing clinical early warning systems. The paradigm has the potential to revolutionize the cardiovascular care paradigm from a generic towards personalized approaches. The second step is to design time-course-interventions based on dynamic predictions with these models, which can potentially enable timing optimization of medication and non-pharmacological intervention.

Conclusions

This work, by providing a new framework in predictive medicine, has opened new avenues in the solution of morning hypertension challenge. The findings firmly establish the fact that this clinical phenomenon does not only have significant prevalence, but also an uncommon hemodynamic pattern as well as risk factors. The physiological difference achieved in the environment of circadian fluctuations in blood pressure emphasizes the need to take a dynamic and time-sensitive approach to managing this disease. Its most spectacular achievement has been the demonstration of the unparalleled potential of deep learning architectures for revealing hidden patterns within richer physiological signals. Its superior performance compared to traditional approaches is irrefutable evidence of the inherent ability of these technologies to identify vulnerable individuals before overt clinical symptoms. The multi-week predictive ability of these models has provided an unprecedented window for preventively directed interventions. The analysis of predictive factors challenged traditionally held concepts regarding blood pressure control. The prominent role of sleep-related parameters and circadian rhythms confirms the significance of incorporating these variables into subsequent screening and monitoring guidelines. This finding is a stimulus to action to go beyond one-dimensional, drug-only models to more holistic models that consider the complex interplay of circadian, everyday routine, and cardiovascular physiology.

The high consistency of the model performance across independent populations is a healthy step toward potential clinical application of this technology. Although challenges in generalizing to certain subgroups were mentioned, the substance of the framework is robust enough to become a viable tool in healthcare. The findings of this study promise four fundamental innovations: first, a shift from reactive to predictive paradigm; second, replacing static indicators with dynamic time-based measures; Third, to bring the significance of sleep parameters to the level of cardinal variables; and fourth, to construct entirely individualized models for management. The practical implications of the field might lead to the creation of smart care systems that have the ca-

pability of optimizing drug scheduling, adaptively modulating therapy dosing, and providing timely behavioral guidance. A next important step will be determining the clinical effectiveness of these predictive interventions for improving cardiovascular outcomes in long-term studies. In contrast, integration with future wearable technologies and electronic health infrastructures will mark the beginning of autonomous ecosystems capable of providing real-time clinical feedback and continuous treatment algorithm optimization. Realization of this vision requires a relentless push toward convergence across multiple specialties. Multidisciplinary collaboration of AI visionaries, cardiologists, health engineers, and health policymakers will be the foundation stone in translating these advances into tangible clinical gains. Only by this can the ultimate outcome of all these efforts be achieved, which is to improve patients' quality of life and reduce the substantial social cost of cardiovascular disease.

References

1. Kario K, Wang JG, Chia Y, Wang TD, Li Y, Siddique S, Shin J, Turana Y, Buranakitjaroen P, Chen CH, Cheng HM, Huynh MV, Nailes J, Sukonthasarn A, Zhang Y, Sison J, Soenarta A, Park S, Sogunuru G, Tay J, Teo B, Tsoi K, Verma N, Hoshide S. The HOPE Asia network 2022 up-date consensus statement on morning hypertension management. J Clin Hypertens (Greenwich). 2022;24(7):736-743. doi:10.1111/jch.14555

2. Tocci G, Sciarretta S, Volpe M. Development of heart failure in recent hypertension trials. J Hypertens. 2008;26(7):1477-1486. doi:10.1097/HJH.0b013e3282fe1d3d

3. Andreadis E, Angelopoulos E, Tsakanikas AP, Agaliotis G, Kravvariti SD, Mousoulis G. Automated office versus home measurement of blood pressure in the assessment of morning hypertension. Blood Press Monit. 2012;17(4):135-138. doi:10.1097/MBP.0b013e3283503760

4. Kario K, Okawara Y, Kanegae H, Hoshide S. Potential long-term benefit of home systolic blood pressure below 125 mm Hg for cardiovascular risk reduction: The J-HOP Study extended. Hypertension. 2023;80(2):315-323. doi:10.1161/HYPERTENSIONAHA.123.22122

5. Al-antari MA. Advancements in artificial intelligence for medical computer-aided diagnosis. Diagnostics (Basel). 2024;14(12):1265. doi:10.3390/diagnostics14121265

6. Abbas S, Sattar A, Shah SH, Hafeez S, Mahmood W, Iqbal R, Shaheen K, Azam P, Shahbaz T. The role of artificial intelligence in personalized medicine and predictive diagnostics – a narrative review. Insights J Health Rehabil. 2025;4(1):1-11. doi:10.71000/k6cga886

7. Layton AT. AI, machine learning, and ChatGPT in hypertension. Hypertension. 2024;81(6):1441-1452. doi:10.1161/HYPERTENSIONAHA.124.19468

8. Kario K, Hoshide S, Mogi M. Hypertension Research global initiatives 2025 added new themes–"implementation hypertension" and "morning hypertension". Hypertens Res. 2025;48(6):885-887. doi:10.1038/s41440-024-02095-7

9. Hermida RC, Crespo JJ, Dominguez-Sardiña M, Otero A, Moyá A, Ríos MT, Sineiro E, Castiñeira M, Callejas PA, Pousa L, Salgado JL, Durán C, Sánchez JJ, Fernández J, Mojón A, Ayala DE. Bedtime hypertension treatment improves cardiovascular risk reduction: the Hygia Chronotherapy Trial. Eur Heart J. 2019;40(40):3081-3090. doi:10.1093/eurheartj/ehz754

10. Sheppard J, Hodgkinson J, Riley R, Martin U, Bayliss S, McManus R. Prognostic significance of the morning blood pressure surge in clinical practice: a systematic review. Am J Hypertens. 2015;28(1):30-41. doi:10.1093/ajh/hpu104

11. Chadachan V, Ye M, Tay J, Subramaniam K, Setia S. Understanding short-term blood-pressure-variability phenotypes: From concept to clinical practice. Int J Gen Med. 2018;11:241-254. doi:10.2147/IJGM.S164903

12. Kario K, Shimbo D, Tomitani N, Kanegae H, Schwartz J, Williams B. The first study comparing a wearable watch-type blood pressure monitor with a conventional ambulatory blood pressure monitor on in-office and out-of-office settings. J Clin Hypertens (Greenwich). 2020;22(8):1354-1362. doi:10.1111/jch.13799

13. Wang JG, Kario K, Park J, Chen CH. Morning blood pressure monitoring in the management of hypertension. J Hypertens. 2017;35(8):1554-1564. doi:10.1097/HJH.0000000000001379

14. Grant S, Collins G, Nashef S. Statistical primer: developing and validating a risk prediction model†. Eur J Cardiothorac Surg. 2018;54(2):254-261. doi:10.1093/ejcts/ezy180

15. Tripepi G, Heinze G, Jager K, Stel V, Dekker F, Zoccali C. Risk prediction models. Nephrol Dial Transplant. 2013;28(8):1975-1984. doi:10.1093/ndt/gft095

16. Lucaroni F, Cicciarella Modica D, Macino M, Palombi L, Abbondanzieri A, Agosti G, Biondi G, Morciano L, Vinci A. Can risk be predicted? An umbrella systematic review of current risk prediction models for cardiovascular diseases, diabetes and hypertension. BMJ Open. 2019;9(12):e030234. doi:10.1136/bmjopen-2019-030234

17. Abrar S, Loo C, Kubota N. A multi-agent approach for personalized hypertension risk prediction. IEEE Access. 2021;9:65854-65867. doi:10.1109/ACCESS.2021.3074791

18. Cui S, Wang J, Gui X, Wang T, Ma F. AUTOMED: Automated medical risk predictive modeling on electronic health records. In: 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM); 2022 Dec 6-9; Las Vegas, NV, USA. IEEE; 2022. p. 3028-3033. doi:10.1109/BIBM55620.2022.9995209