Hypertension

REVIEW

Artificial Intelligence in Cardiovascular Medicine: Focus on Hypertension

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ABSTRACT: Hypertension remains the most prevalent modifiable risk factor for cardiovascular morbidity and mortality worldwide, yet rates of effective blood pressure control remain persistently suboptimal despite the availability of multiple therapeutic options. This gap reflects fundamental limitations of current care models, which rely on episodic measurements, population-based treatment algorithms, and incomplete representation of the biological, behavioral, and social complexity underlying blood pressure regulation. Artificial intelligence (AI) offers a transformative framework to address these challenges by enabling the integration of longitudinal, multimodal data and modeling nonlinear, dynamic relationships that are difficult to capture with conventional approaches. This systematic review synthesizes emerging evidence on the application of AI across the hypertension care continuum, including risk prediction, phenotyping, blood pressure measurement, wearable-based monitoring, clinical trial analysis, population health modeling, detection of secondary hypertension, behavioral and adherence interventions, and multi-omics–driven precision medicine. We highlight the methodological foundations required for clinically meaningful AI, emphasizing robust ground-truth definitions, external and temporal validation, interpretability, workflow integration, and equity-aware design. The review also examines the promise and limitations of natural language processing, cuffless blood pressure technologies, and AI-guided decision support systems, alongside ethical, regulatory, and implementation challenges. Collectively, current evidence suggests that AI has the potential to shift hypertension management from a reactive, threshold-based paradigm toward a more predictive, personalized, and patient-centered model. Realizing this potential will depend on rigorous validation, thoughtful implementation, and sustained alignment with clinical, ethical, and equity principles.

Key Words: artificial intelligence ■ blood pressure ■ machine learning ■ precision medicine ■ risk factors

Hypertension remains the most prevalent modifiable risk factor for cardiovascular morbidity and mortality worldwide and continues to impose a substantial clinical and public health burden despite decades of therapeutic advances. Global estimates indicate that more than 1 billion adults are affected, yet rates of awareness, treatment, and effective blood pressure (BP) control remain persistently suboptimal.[1] Even in high-income countries with broad access to health care, fewer than half of treated patients achieve recommended BP targets.[2] This persistent gap between available therapies and real-world outcomes highlights fundamental limitations in current hypertension care paradigms and underscores the need for more precise, adaptive, and scalable approaches.

A central challenge in hypertension management is the intrinsic complexity and heterogeneity of BP regulation. BP is a dynamic physiological variable influenced by genetic predisposition, neurohormonal signaling, vascular structure, renal function, lifestyle behaviors, psychosocial stress, environmental exposures, and social determinants of health. Traditional clinical models, which rely largely on episodic office measurements and population-based treatment algorithms, are poorly equipped to capture this multidimensional and time-varying complexity.[3] As a result, clinically meaningful patterns such as masked hypertension, nocturnal nondipping, exaggerated BP variability, and heterogeneous treatment responses often remain undetected.[4] These limitations contribute to delayed diagnosis, inappropriate therapeutic intensification or inertia, and residual cardiovascular risk.

Artificial intelligence (AI) offers a fundamentally different analytic framework capable of addressing many of these challenges. By design, AI systems can integrate high-dimensional data from diverse sources, including electronic health records (EHRs), laboratory results,

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Hypertension is available at www.ahajournals.org/journal/hyp

Nonstandard Abbreviations and Acronyms

AI	artificial intelligence
BP	blood pressure
EHR	electronic health record
LLM	large language model
ML	machine learning
NLP	natural language processing

imaging, wearable sensors, genomics, and environmental data, while modeling nonlinear relationships and interactions that are difficult to capture using conventional statistical approaches.[5–7] In hypertension, this capacity enables the identification of latent phenotypes, risk trajectories, and response patterns that extend beyond traditional classifications based on static BP thresholds.

A key rationale for AI in hypertension lies in the longitudinal nature of the disease.[8] Hypertension typically develops over years or decades, progressing from subtle BP elevations to sustained hypertension and ultimately to hypertension-mediated organ damage. Conventional clinical encounters provide only sparse snapshots of this trajectory, limiting opportunities for early intervention.[9] AI models trained on longitudinal data can detect early deviations from individual baselines, characterize BP trajectories over time, and identify individuals at risk for progression before clinical thresholds are crossed. This capability supports a shift toward earlier, more proactive management strategies.

AI is also well-suited to addressing variability in treatment response, a persistent challenge in hypertension care. Patients with similar baseline BP and comorbidity profiles often respond differently to the same antihypertensive therapy, reflecting underlying biological and behavioral heterogeneity. AI-based analyses of clinical trial and real-world data have demonstrated substantial heterogeneity in treatment effects, suggesting that uniform BP targets and stepwise treatment algorithms may not be optimal for all patients.[10–12] These insights provide a rationale for AI-driven precision approaches aimed at tailoring therapy intensity and drug selection to individual risk-benefit profiles. From a systems perspective, AI also offers tools to improve population-level hypertension management. Health systems increasingly rely on large-scale electronic data repositories, yet extracting actionable insights from these data sets remains challenging. AI models can be applied to identify patients with uncontrolled hypertension, predict health care utilization, and support risk stratification at scale.[13] When coupled with clinical decision support, these tools have the potential to enhance guideline adherence, reduce therapeutic inertia, and optimize resource allocation across populations. Importantly, the rationale for AI in hypertension is not limited to technical performance but extends to addressing equity and access.

Hypertension disproportionately affects older adults, racial and ethnic minorities, and individuals with lower socioeconomic status, groups that are often underrepresented in clinical trials and underserved by traditional care models.[14] Different AI systems (described in detail in Table 1), when developed and validated responsibly, offer the potential to identify high-risk individuals earlier and support targeted interventions. At the same time, inappropriate use of AI risks reinforcing existing disparities, underscoring the importance of ethical and equitable design from the outset.

Therefore, the rationale for applying AI to hypertension care rests on the mismatch between the complexity of BP regulation and the limitations of current clinical approaches. By enabling integration of longitudinal, multimodal data and supporting individualized risk assessment and treatment strategies, AI has the potential to transform hypertension management from a reactive, population-based model to a more precise, predictive, and patient-centered paradigm.[15–17] Whether this potential translates into improved outcomes will depend on rigorous validation, thoughtful implementation, and sustained alignment with clinical and ethical principles.

METHODS

This systematic review, registered in PROSPERO (Prospective Register Of Systematic Reviews; CRD420261296095), was conducted to identify and synthesize original studies applying AI, including machine learning (ML) and deep learning, to hypertension detection, classification, risk prediction, prognosis, treatment optimization, and clinical decision support in adult populations. We searched PubMed/MEDLINE, Embase, Web of Science, Scopus, and the Cochrane Library from inception without date or language restrictions using combinations of the following keywords and related terms: “hypertension,” “high blood pressure,” “artificial intelligence,” “machine learning,” “deep learning,” “neural network,” “predictive modeling,” “risk prediction,” “classification,” “detection,” and “clinical decision support.” Reference lists of eligible articles were also screened. Observational studies and clinical trials applying AI-based approaches were included, with comparators consisting of conventional clinical assessment, traditional statistical models, established risk scores, or no AI approach; reviews were used only to identify additional references. Primary outcomes were model performance metrics (eg, discrimination, calibration, accuracy) and measures of clinical utility, including impact on BP control or treatment decisions, while secondary outcomes included data sources, algorithm types, development and validation strategies, and reported limitations or biases. Two investigators independently screened studies, extracted data, and assessed risk of bias using Prediction Model Risk of Bias Assessment Tool for predictive models and the Newcastle–Ottawa Scale for observational studies, resolving discrepancies by consensus. Given expected heterogeneity in populations, data modalities, algorithms, and outcome reporting, findings were synthesized narratively, emphasizing methodological rigor, external validation, interpretability, and clinical applicability.

Table 1. Artificial Intelligence Nomenclature and Methodological Approaches in Hypertension Research.

Term	Definition	Typical applications in hypertension	Data sources	Key strengths	Key limitations
AI	A broad term describing computational systems that perform tasks requiring human intelligence	Risk prediction, phenotyping, decision support	EHRs, trials, wearables	Integrates complex, multimodal data	Conceptually broad; heterogeneous methods
ML	A subset of AI in which algorithms learn patterns from data	Incident hypertension prediction; BP control modeling	EHRs, cohorts	Flexible; scalable	Dependent on data quality and labeling
Supervised learning	Machine learning using labeled input–output pairs	Prediction of BP control; secondary hypertension detection	EHRs, registries	Direct clinical prediction	Requires accurate ground truth
Unsupervised learning	Machine learning identifying patterns without predefined labels	BP trajectory clustering; phenotype discovery	Longitudinal BP data	Identifies latent subgroups	Limited clinical interpretability
Penalized regression	Regression with regularization to reduce overfitting	hypertension risk prediction; feature selection	Cohorts, EHRs	Transparent; clinically interpretable	Limited nonlinear modeling
Random forests	Ensemble of decision trees	Risk stratification; secondary hypertension screening	EHRs, trials	Captures nonlinear interactions	Reduced interpretability
Gradient boosting machines	Sequential tree-based ensemble learning	BP control prediction; population modeling	EHRs, claims	High predictive accuracy	Calibration challenges
Support vector machines	Margin-based classification/regression	hypertension classification; phenotype discrimination	Cohorts, wearables	Effective in high-dimensional data	Parameter sensitivity; opacity
Neural networks and deep learning	Multi-layered neural architectures	BP estimation; wearable signal analysis	Wearables, physiological data	Captures complex temporal patterns	Large data needs; black-box behavior
NLP	AI methods for extracting information from free text	hypertension phenotyping; adherence detection	Clinical notes	Unlocks unstructured EHR data	Language variability
Predictive modeling	AI-based forecasting of future outcomes	Incident hypertension; progression risk	Longitudinal data sets	Enables early intervention	Requires external validation
Phenotyping	Data-driven classification into subgroups	Masked hypertension; resistant hypertension	BP trajectories, EHRs	Supports precision care	Often exploratory
Causal inference methods	AI/statistical tools estimating treatment effects	Individualized BP targets	Trials, registries	Addresses heterogeneity of effects	Strong assumptions required
XAI	Methods improving the interpretability of AI outputs	Clinical decision support	EHR-based models	Improves clinician trust	Partial transparency only
Human-in-the-loop AI	AI systems supporting, not replacing, clinicians	BP management decision support	Clinical workflows	Enhances safety and accountability	Requires workflow integration
Digital twin	Virtual patient model simulating interventions	Treatment response modeling	Multimodal longitudinal data	Personalized simulation	Largely experimental

AI indicates artificial intelligence; BP, blood pressure; EHR, electronic health records; ML, machine learning; NLP, Natural language processing; and XAI, explainable AI.

METHODOLOGICAL FOUNDATIONS OF AI IN HYPERTENSION: FROM ALGORITHM DEVELOPMENT TO CLINICAL RELEVANCE

The successful application of AI to hypertension hinges on methodological rigor, transparency, and clinical relevance. Although early studies often emphasized algorithmic novelty or statistical performance, it has become increasingly clear that model development must be grounded in robust data curation, appropriate validation strategies, and clinically meaningful end points to ensure translational value. Hypertension represents a particularly challenging domain for AI because BP is a dynamic, context-dependent physiological variable influenced by behavioral, environmental, and biological factors that are inconsistently captured in clinical data sets.

ML methods applied to hypertension span supervised, unsupervised, and deep learning approaches, including logistic regression extensions, random forests, gradient boosting machines, support vector machines, and neural networks.[18] Supervised learning remains the most widely used paradigm, particularly for predicting incident hypertension, classifying BP phenotypes, or estimating treatment response. Ensemble-based methods and tree-based algorithms frequently outperform traditional regression, largely due to their ability to model nonlinear relationships and higher-order interactions among predictors.[19,20]

A central methodological concern in hypertension-focused AI research is the definition of ground truth. BP labels are often derived from office measurements recorded in EHRs, which are susceptible to white-coat effects, masked hypertension, measurement error, and inconsistent protocols. These limitations introduce noise and misclassification that can propagate through training pipelines and inflate apparent model performance. Models trained exclusively on office BP readings exhibit reduced accuracy when applied to ambulatory or home BP data, underscoring the importance of integrating longitudinal and out-of-office measurements whenever possible.[21]

Validation strategies represent another critical determinant of model credibility. Many early AI studies in hypertension relied on internal validation alone, typically using random train-test splits that fail to account for temporal drift, practice variation, or population differences. Contemporary guidance increasingly emphasizes the necessity of external validation across independent cohorts and health care systems, as well as temporal validation that reflects real-world deployment conditions. In cardiovascular medicine more broadly, lack of external validation has been identified as a major barrier to clinical adoption of AI tools, with hypertension serving as a paradigmatic example.[22] There is growing consensus that AI models must be evaluated using clinically actionable outcomes including sustained BP control, reduction in BP variability, prevention of progression to stage 2 hypertension, and mitigation of hypertension-mediated organ damage. Models demonstrating excellent statistical performance but lacking linkage to downstream clinical decisions or outcomes are unlikely to improve care, regardless of their computational sophistication.[23] Model interpretability is particularly important in hypertension management, where therapeutic decisions are nuanced and often require clinician judgment. Black-box models that provide predictions without explanatory context risk undermining clinician trust and may obscure biases embedded in training data. Interpretable ML techniques, including feature importance analyses, SHAP (Shapley Additive explanations) values, and causal inference frameworks, have therefore gained prominence.[24] These approaches allow clinicians to understand how specific factors (such as age, body mass index, renal function, medication adherence, and socioeconomic variables) contribute to predicted hypertension risk or treatment response.[25] Clinical deployment further requires integration into existing workflows and EHR systems. Studies evaluating AI-based clinical decision support for hypertension have shown that standalone tools, even when accurate, are rarely adopted unless seamlessly embedded into clinical workflows and accompanied by clear recommendations rather than abstract risk scores.[26] Importantly, human-in-the-loop designs, in which clinicians retain decision authority while being augmented by AI-generated insights, have been proposed as a pragmatic and ethically sound model for hypertension care.[27] Regulatory and ethical considerations also shape methodological standards. Because hypertension disproportionately affects minorities, elderly, and socioeconomically disadvantaged populations, AI models trained on nonrepresentative data sets risk perpetuating or amplifying existing disparities.[28] Methodological frameworks increasingly recommend stratified performance analyses and bias audits to ensure equitable model behavior across demographic subgroups. This concern has been echoed in recent consensus statements on trustworthy AI in cardiovascular medicine, which emphasize transparency, accountability, and fairness as core methodological principles.[29,30] Methodological excellence in AI-driven hypertension research requires far more than algorithmic performance: robust ground-truth definitions, external and temporal validation, clinically meaningful end points, interpretability, workflow integration, and equity-aware design are all essential prerequisites for translation. Without adherence to these principles, AI risks remaining an academic exercise rather than a transformative tool in hypertension care. Recent reports have also shown the application of AI to pulmonary hypertension[31–49] and to portal hypertension.[50–54]

NATURAL LANGUAGE PROCESSING AND EHR-DERIVED PHENOTYPING IN HYPERTENSION

EHRs are among the richest data sources for AI applications in hypertension, yet much of its clinically relevant content resides in unstructured free-text narratives rather than structured fields. Progress notes, discharge summaries, referral letters, and nursing documentation frequently contain essential information regarding lifestyle behaviors, medication adherence, adverse drug reactions, psychosocial stressors, and clinician reasoning that is either incompletely coded or absent from structured data sets. Natural language processing (NLP), a core subfield of AI, has, therefore, emerged as a critical tool for unlocking this latent information and enabling more precise hypertension phenotyping.[43]

Early NLP applications in cardiovascular medicine focused on rule-based systems and keyword extraction, but these approaches proved brittle and poorly generalizable across institutions. More recent methods leverage ML and deep learning architectures, including word embeddings and transformer-based models, to capture semantic context and clinical nuance. In hypertension, NLP has been used to identify patients with undiagnosed or poorly controlled disease, extract longitudinal BP trends described narratively, and detect clinician-documented barriers to BP control, such as medication intolerance or socioeconomic constraints.

One of the most impactful applications of NLP in hypertension has been the identification of disease status and phenotypes that are not reliably captured by diagnostic codes. *International Classification of Diseases* codes for hypertension have limited sensitivity and specificity, particularly in patients with borderline BP values, masked hypertension, or intermittent elevations.[55] Studies using NLP to analyze clinical notes have demonstrated improved case detection and more accurate classification of hypertension severity compared with code-based approaches alone.[56,57] Beyond disease identification, NLP enables the extraction of behavioral and contextual determinants of BP that are otherwise difficult to quantify. Diet, physical activity, alcohol intake, sleep quality, stress, and medication adherence are frequently described qualitatively in clinician notes but rarely captured as structured variables.[58,59] ML models incorporating NLP-derived features reflecting these domains have shown improved performance in predicting hypertension onset and poor BP control. Of note, ML models integrating unstructured EHR data consistently outperformed those relying solely on structured variables.[19,60,61]

NLP has also been applied to longitudinal EHR data to model disease trajectories. Hypertension is not a static diagnosis but rather a progressive condition characterized by evolving treatment strategies, fluctuating BP control, and cumulative organ damage. NLP allows the extraction of temporal information such as treatment intensification, clinician concern about rising BP, or documentation of resistant hypertension, enabling dynamic phenotyping over time. Studies using temporal NLP frameworks have demonstrated the feasibility of identifying patients at risk for progression to resistant hypertension before formal diagnostic thresholds are met. The integration of NLP with large language models (LLMs) represents a recent and potentially transformative development. LLMs can summarize longitudinal clinical narratives, reconcile conflicting information across notes, and generate structured representations suitable for downstream ML tasks.[62–67] Early evaluations suggest that such models may substantially reduce the burden of manual chart review while preserving clinical nuance. However, concerns regarding hallucinations, bias, and reproducibility remain significant, particularly in high-stakes applications, such as hypertension management, where incorrect inferences could lead to inappropriate treatment decisions.[68,69] LLMs are currently better suited for summarization and phenotyping support than autonomous decision-making.

LLMs and small language models differ primarily in scale, capability, and deployment trade-offs. LLMs are trained on very large data sets with billions of parameters, enabling broad language understanding, complex reasoning, and strong generalization across diverse tasks, but they require substantial computational resources and infrastructure. In contrast, small language models use far fewer parameters and more limited training data, making them faster, cheaper, and easier to deploy on edge devices or in resource-constrained environments,[70] albeit with reduced linguistic breadth and reasoning depth.

From a clinical perspective, NLP-derived phenotyping has important implications for equity and population health. Social determinants of health, including housing instability, food insecurity, and limited access to care, are frequently documented narratively rather than in structured fields. NLP provides a mechanism to systematically capture these factors and incorporate them into risk stratification and care planning. This capability is particularly relevant in hypertension, where social and environmental factors play a major role in disease development and control. Ethical frameworks for AI in cardiovascular medicine increasingly emphasize the importance of leveraging unstructured data to avoid systematic exclusion of vulnerable populations.

Despite its promise, NLP-based hypertension phenotyping faces several challenges.[71] Clinical language varies across institutions, specialties, and individual clinicians, necessitating careful model training and validation. Data privacy concerns, computational requirements, and the need for continuous model updating further complicate deployment. Nonetheless, the growing maturity of NLP methods and their demonstrated ability to extract clinically actionable information position them as a cornerstone of future AI-driven hypertension care.

So, NLP enables a shift from code-based hypertension classification toward richer, context-aware phenotyping that better reflects real-world clinical complexity. By integrating narrative data with structured EHR elements, NLP-enhanced AI models offer a more comprehensive understanding of hypertension risk, progression, and treatment response, thereby supporting more personalized and equitable management strategies.

BP MEASUREMENT: LIMITATIONS OF OFFICE-BASED ASSESSMENT AND THE EMERGENCE OF AI-ENABLED CUFFLESS TECHNOLOGIES

Accurate BP measurement is foundational to the diagnosis and management of hypertension, yet it remains one of the most problematic aspects of clinical care. Conventional office-based BP measurements, despite their widespread use, are subject to substantial variability arising from measurement technique, observer bias, patient anxiety, environmental context, and temporal fluctuations. These limitations have long been recognized, but their implications become particularly consequential when office BP values are used as ground truth labels for AI models. As a result, AI systems trained on office-based measurements risk learning noise rather than true physiological signals.

White-coat hypertension and masked hypertension exemplify the shortcomings of office BP assessment. White-coat hypertension, characterized by elevated clinic BP with normal out-of-office values, and masked hypertension, in which clinic BP appears normal despite elevated ambulatory or home BP, are both associated with distinct cardiovascular risk profiles. Large observational studies and meta-analyses have demonstrated that masked hypertension carries a cardiovascular risk comparable to sustained hypertension, whereas white-coat hypertension confers an intermediate risk. These phenomena undermine the reliability of clinic BP as a reference standard and pose significant challenges for AI-driven prediction and classification models.[72–75]

Ambulatory BP monitoring and home BP monitoring provide superior prognostic information compared with office measurements, particularly for predicting cardiovascular events and target-organ damage. Ambulatory BP captures circadian patterns, nocturnal dipping status, and short-term variability, all of which are powerful predictors of adverse outcomes. AI models incorporating ambulatory or longitudinal home BP data have demonstrated improved performance in identifying high-risk hypertension phenotypes compared with models trained solely on clinic measurements. However, widespread adoption of ambulatory monitoring remains limited by cost, patient burden, and logistical constraints.[76] The emergence of AI-enabled cuffless BP technologies represents an attempt to overcome these limitations by enabling continuous, unobtrusive BP assessment (Table 2). These systems typically rely on surrogate physiological signals, such as photoplethysmography, electrocardiography, pulse transit time, pulse arrival time, or combinations thereof, with ML algorithms used to estimate BP values. Advances in wearable sensors and deep learning have accelerated development in this area, leading to growing interest from both researchers and commercial entities.[77] Despite promising early results, cuffless BP estimation remains scientifically and clinically contentious. Many models demonstrate acceptable accuracy in controlled laboratory settings but perform poorly when applied across diverse populations, varying physiological states, or real-world conditions involving motion artifacts and environmental noise. A major challenge lies in calibration, as most cuffless systems require periodic reference measurements, limiting their independence from traditional cuff-based devices. Interindividual variability in vascular stiffness, arterial geometry, and autonomic tone further complicates model generalizability. AI-enabled cuffless BP technologies are not currently guideline-endorsed for diagnosis or treatment titration, and consensus statements have emphasized that cuffless devices should not replace validated BP measurement methods in routine clinical care.[78]

From an AI perspective, the use of cuffless BP data introduces complex methodological considerations. Models trained to estimate absolute BP values may propagate systematic biases, whereas models focused on relative changes or trend detection may offer greater clinical utility. Some investigators have proposed that the primary value of cuffless technologies lies not in precise BP estimation but in identifying deviations from an individual's baseline or detecting loss of BP control over time. This paradigm shift aligns with emerging concepts of personalized longitudinal monitoring rather than population-based thresholds.[79,80]

Regulatory and validation frameworks for cuffless BP technologies are still evolving. Traditional validation protocols were designed for cuff-based devices and may be ill-suited for AI-driven systems that adapt over time. Regulatory agencies and professional societies have called for standardized validation methodologies that account for demographic diversity, comorbid conditions, and real-world use scenarios. The lack of such standards remains a major barrier to clinical adoption and contributes to skepticism

Table 2. BP Measurement Modalities and Integration With Artificial Intelligence

BP measurement modality	Data characteristics	Role of AI	Clinical advantages	Major limitations	Validation status
Office BP	Sparse, episodic, protocol-dependent	Risk stratification; phenotyping	Widely available; guideline-based	White-coat effect; masked hypertension; poor longitudinal resolution	Fully validated, but limited prognostic precision
Home BP monitoring	Repeated self-measurements	Trajectory analysis; adherence detection	Better prognostic value than office BP	Patient technique variability; incomplete adherence	Validated for diagnosis and management
Ambulatory BP monitoring	Continuous 24-hour profiles	Circadian pattern analysis; phenotype classification	Strong outcome prediction; detects masked hypertension	Cost; patient burden	Gold standard for out-of-office BP
Wearable physiological signals	High-frequency, real-world data	Indirect BP trend modeling	Longitudinal monitoring; context awareness	Signal noise; motion artifacts; indirect estimation	Limited clinical validation
Cuffless BP estimation (AI-based)	Surrogate cardiovascular signals	BP estimation or trend detection	Potential for continuous monitoring	Calibration dependence; interindividual variability	Not recommended for routine clinical use
Longitudinal BP trajectories	Time-series BP data	Variability and progression modeling	Captures disease dynamics	Data completeness requirements	Supported in observational studies

AI indicates artificial intelligence; and BP, blood pressure.

among clinicians.[81] Equity considerations are particularly salient in this domain. Skin tone, peripheral perfusion, and vascular disease can affect photoplethysmographic signals, raising concerns about differential accuracy across racial and ethnic groups. AI models trained on nonrepresentative data sets risk exacerbating disparities in hypertension diagnosis and management if deployed at scale without appropriate bias assessment and mitigation strategies.[28] These concerns mirror broader discussions on fairness in digital cardiovascular health.

Although office-based BP measurement remains deeply entrenched in clinical practice, its limitations constrain both conventional care and AI-driven innovation. Ambulatory and home BP monitoring provide superior physiological insight but face implementation barriers. AI-enabled cuffless technologies offer an intriguing vision of continuous BP monitoring, yet substantial scientific, methodological, and regulatory challenges remain unresolved. Future progress will depend on rigorous validation, transparency in algorithm development, and careful integration into clinical workflows, with a focus on augmenting rather than replacing established measurement standards.

WEARABLES, LONGITUDINAL MONITORING, AND AI-GUIDED BP CONTROL

The increasing availability of wearable devices capable of continuous physiological monitoring has created new opportunities for AI to transform BP management from episodic assessment to longitudinal care. Unlike traditional clinic-based encounters, wearables generate high-frequency, real-world data streams that capture physiological variability across daily activities, sleep, stress, and environmental exposures. In hypertension, this shift from static to dynamic monitoring is particularly relevant, as BP regulation is inherently time-dependent and influenced by behavioral and contextual factors that are poorly represented in conventional clinical data sets.

Wearable devices commonly collect signals, such as heart rate, physical activity, sleep metrics, and photoplethysmography-derived pulse waveforms. When analyzed using AI methods, these signals can provide indirect insights into BP regulation and cardiovascular autonomic function. Several studies have demonstrated that ML models integrating wearable-derived features can identify individuals with uncontrolled hypertension or predict future elevations in BP with moderate to high accuracy. Importantly, these models often outperform traditional risk stratification approaches that rely on sparse clinic measurements alone.[82–91]

Longitudinal monitoring enabled by wearables allows for characterization of BP variability, a parameter increasingly recognized as an independent risk factor for cardiovascular events. Visit-to-visit and short-term BP variability have been associated with stroke, coronary disease, and mortality, independent of mean BP levels.[92] AI models applied to continuous or near-continuous wearable data can quantify variability patterns, identify abnormal trajectories, and detect early deviations from an individual's baseline that may signal loss of BP control or poor adherence.[12,93,94]

AI has also been applied to wearable data to support treatment optimization and adherence monitoring. Changes in physical activity patterns, sleep duration, or heart rate dynamics following antihypertensive therapy initiation can provide indirect markers of treatment response or adverse effects. ML approaches capable of integrating these signals over time may allow clinicians to distinguish true pharmacological nonresponse from poor adherence or lifestyle-related BP fluctuations.[95–101]

Despite these promising applications, several challenges limit the current clinical impact of wearable-based AI systems in hypertension. Data quality remains a major concern, as consumer-grade devices vary widely in sensor accuracy, sampling frequency, and robustness to motion artifacts. Missing data, device nonwear, and user disengagement introduce biases that can degrade model performance over time. Moreover, most wearable-based studies have been conducted in relatively healthy, technologically engaged populations, raising concerns about generalizability to older adults, individuals with multimorbidity, or socioeconomically disadvantaged groups who bear a disproportionate burden of hypertension.

Integration of wearable-derived AI insights into clinical workflows represents another critical barrier. Clinicians face substantial cognitive and administrative burdens, and additional data streams risk exacerbating information overload unless translated into concise, actionable recommendations. Studies evaluating clinician-facing dashboards for wearable data have shown that adoption depends heavily on interpretability, relevance to decision-making, and alignment with existing care pathways. AI systems that merely report trends without clinical context are unlikely to influence hypertension management meaningfully.

Regulatory and ethical considerations further complicate the deployment of AI-guided wearable systems. Many algorithms are continuously learning, raising questions about version control, reproducibility, and regulatory oversight. Additionally, wearable-derived data often originates outside traditional health care settings, creating challenges related to data ownership, privacy, and consent. These issues are particularly salient in hypertension, where long-term monitoring may be required across decades of care.

Unfortunately, access to wearable technology is uneven, and reliance on such devices risks excluding populations with limited digital literacy or financial resources. AI models trained predominantly on data from wearable users may therefore underperform in precisely those populations at highest cardiovascular risk.[102] Addressing this concern will require deliberate efforts to include diverse cohorts in wearable-based hypertension research and to design AI systems that complement, rather than replace, traditional care pathways.

Hence, wearable devices combined with AI offer a powerful framework for longitudinal BP monitoring and adaptive hypertension management. By capturing real-world physiological variability, these systems have the potential to improve risk stratification, detect early loss of BP control, and support personalized treatment strategies. However, substantial challenges related to data quality, workflow integration, equity, and regulatory oversight must be addressed before wearable-based AI can be fully integrated into routine hypertension care.

AI APPLIED TO CLINICAL TRIAL DATA AND POPULATION-LEVEL HYPERTENSION MODELING

Randomized clinical trials and large population-based cohorts represent some of the most valuable data sources for advancing hypertension care, yet their complexity and scale pose analytical challenges that exceed the capabilities of traditional statistical approaches. AI offers powerful tools for extracting deeper insights from these data sets by modeling nonlinear relationships, high-order interactions, and heterogeneity of treatment effects. In hypertension research, AI-driven analyses of trial and population data have been increasingly used to refine risk stratification, identify responder subgroups, and simulate personalized treatment strategies.[103–105] ML approaches applied to clinical trials have included random forests, gradient boosting machines, and causal inference frameworks designed to estimate individualized treatment effects; these methods attempt to move beyond average treatment effects toward precision hypertension, in which BP targets and treatment intensity are tailored to patient-specific risk profiles.[106–111] These approaches can identify patient subsets with differential risk-benefit trade-offs, although prospective validation remains limited. AI has been extensively applied to large observational cohorts and real-world data sets to model hypertension prevalence, incidence, and outcomes at the population level.[112,113] National health surveys, insurance claims databases, and EHR repositories provide longitudinal data on millions of individuals, enabling ML models to detect patterns and trends that inform public health strategies; AI-based population models have been used to predict geographic variation in hypertension burden, forecast future prevalence under different intervention scenarios, and identify communities at heightened risk due to socioeconomic and environmental factors.[114,115]

A major advantage of AI in population-level hypertension modeling is its ability to integrate diverse data sources, including clinical variables, demographic characteristics, environmental exposures, and social determinants of health. Studies incorporating neighborhood-level deprivation indices, air pollution data, and access to health care services have demonstrated improved prediction of hypertension incidence and control rates compared with models based on clinical data alone.[116] These findings highlight the potential of AI to inform targeted prevention strategies and resource allocation.

Despite these advances, the application of AI to trial and population data raises important methodological and interpretative challenges. Clinical trial data sets are typically curated under strict protocols and may not reflect real-world populations, limiting the external validity of AI-derived insights. Conversely, observational data sets are subject to confounding, missing data, and measurement bias, which can mislead ML models if not appropriately addressed.[110,117] AI-driven subgroup discovery in trials may generate spurious findings unless guided by sound causal reasoning and subjected to rigorous validation.

Another emerging application is the use of AI to simulate hypothetical treatment scenarios and policy interventions at the population level. Digital twin models and counterfactual simulations have been proposed as tools to estimate the impact of alternative BP targets, medication strategies, or screening programs on cardiovascular outcomes.[13] Although conceptually appealing, these approaches remain largely experimental and depend heavily on the quality and completeness of underlying data.

Ethical considerations are particularly salient when AI is applied to population-level hypertension modeling. Decisions informed by such models may influence public health policy, reimbursement, and access to care. If models are trained on biased or incomplete data, they risk reinforcing existing health disparities.[118,119] What is needed is instead transparency, stakeholder engagement, and ongoing monitoring of AI systems used in population health applications.

In summary, AI has expanded the analytical toolkit available for extracting value from hypertension trials and large-scale population data sets. By uncovering heterogeneity of treatment effects, modeling complex interactions, and integrating multilevel determinants of health, AI has the potential to inform more nuanced clinical guidelines and public health strategies. However, careful methodological design, causal awareness, and prospective validation are essential to ensure that AI-derived insights translate into meaningful improvements in hypertension outcomes.

AI FOR THE PREDICTION AND PREVENTION OF INCIDENT HYPERTENSION

Preventing the development of hypertension represents a critical yet underdeveloped frontier in cardiovascular medicine. Traditional risk assessment approaches rely on static factors such as age, body mass index, family history, and baseline BP, which capture only a portion of an individual's lifetime risk. AI offers the potential to identify high-risk individuals earlier and more accurately by integrating longitudinal, multidimensional data and modeling complex, nonlinear trajectories that precede the clinical onset of hypertension.[29,120,121]

ML models for predicting incident hypertension have been developed using a wide range of data sources, including EHRs, health surveys, wearable devices, and population registries.[122,123] These models commonly employ algorithms, such as random forests, gradient boosting machines, and neural networks, to capture interactions among demographic, clinical, behavioral, and laboratory variables.

Longitudinal data play a central role in AI-based prediction of hypertension. Rather than relying on single baseline measurements, ML models can incorporate temporal patterns of BP, weight change, physical activity, and metabolic markers to identify trajectories associated with future hypertension. Subtle increases in systolic BP, rising BP variability, and changes in heart rate dynamics often precede the clinical diagnosis of hypertension, suggesting a window of opportunity for early intervention.[92]

The integration of wearable-derived data has further enhanced predictive performance in some models. Continuous monitoring of activity, sleep, and physiological signals provides context-rich information that reflects daily behaviors and stress responses influencing BP regulation. AI models leveraging these data streams have been able to identify individuals at elevated risk for hypertension who would not be flagged by conventional risk assessment tools. These findings support the concept that hypertension risk is dynamic and modifiable, rather than fixed by baseline characteristics alone.[124]

AI also enables identification of specific hypertension phenotypes during the preclinical phase. Masked hypertension, stress-related BP elevations, and early autonomic dysregulation are often missed in routine care but can be inferred from longitudinal patterns detected by AI. Recognizing these phenotypes early may allow for targeted lifestyle or pharmacological interventions before sustained hypertension develops.

From a prevention standpoint, AI-driven risk prediction models have the potential to inform personalized intervention strategies. Rather than applying uniform lifestyle recommendations to broad populations, AI could identify which individuals are most likely to benefit from specific interventions, such as weight loss, dietary sodium reduction, increased physical activity, or stress management. Early studies using ML to model response to lifestyle interventions suggest that personalized approaches may yield greater BP reductions than generic recommendations, although robust prospective trials are still needed.[125,126] Despite these advances, several challenges limit the current utility of AI for hypertension prevention. Many predictive models are developed and validated retrospectively, raising concerns about overfitting and optimism bias. External validation across diverse populations remains inconsistent, and few models have been tested in prospective interventional settings. Furthermore, predictive accuracy does not automatically translate into improved outcomes unless coupled with effective, scalable prevention strategies and patient engagement.

Ethical and equity considerations are especially important in preventive applications. AI-based risk prediction could inadvertently stigmatize individuals or communities labeled as high risk, especially if underlying social determinants are not addressed. Conversely, failure to include diverse populations in model development may result in underestimation of risk in groups already disproportionately affected by hypertension. Ethical frameworks for AI in preventive cardiology emphasize transparency, fairness, and shared decision-making to ensure that predictive tools support, rather than undermine, patient-centered care.

AI has demonstrated considerable promise in predicting the development of hypertension well before clinical diagnosis, enabling a shift toward earlier and more precise prevention strategies. By integrating longitudinal clinical data, wearable-derived signals, and behavioral information, AI-based models can identify high-risk trajectories and inform personalized interventions. Realizing this potential will require prospective validation, integration with preventive care programs, and careful attention to ethical and equity considerations.

AI FOR THE IDENTIFICATION OF SECONDARY HYPERTENSION

Secondary hypertension accounts for a minority of hypertension cases overall, yet it represents a clinically critical subgroup because targeted treatment can be curative or substantially modify disease trajectory. Despite its importance, secondary hypertension remains markedly underdiagnosed in routine practice, largely due to nonspecific clinical presentations, fragmented diagnostic pathways, and limited clinician awareness. AI offers a promising approach to improving detection by systematically analyzing complex clinical patterns that are difficult to recognize through conventional evaluation alone.

Primary aldosteronism is the most common form of secondary hypertension and exemplifies the diagnostic challenges that AI may help overcome. Epidemiological studies suggest that primary aldosteronism affects a substantial proportion of patients with resistant or severe hypertension, yet the majority of cases remain undiagnosed. AI-based models leveraging EHR data have demonstrated the ability to identify patients at high likelihood of primary aldosteronism by integrating laboratory values, medication patterns, BP trajectories, and comorbidities. These models can flag candidates for confirmatory testing earlier and more consistently than rule-based screening approaches.[127,128]

ML approaches applied to primary aldosteronism detection often use ensemble methods or penalized regression to account for correlated predictors and missing data. Variables such as hypokalemia, suppressed renin activity, resistant hypertension, and early onset disease contribute to model predictions, but AI systems can also detect subtler patterns, including medication escalation trajectories and repeated borderline laboratory abnormalities.[129,130]

Beyond primary aldosteronism, AI has been explored for identifying other causes of secondary hypertension, including renal artery stenosis, chronic kidney disease–related hypertension, and endocrine disorders such as Cushing syndrome and pheochromocytoma.[8,131,132] Although these conditions are less prevalent, delayed diagnosis carries substantial morbidity. AI models trained on large EHR data sets can integrate imaging reports, biochemical data, and clinical notes to identify patients with patterns suggestive of secondary etiologies who may benefit from targeted evaluation.

NLP plays a particularly important role in this context, as many diagnostic clues for secondary hypertension are embedded in unstructured clinical narratives. References to episodic symptoms, refractory BP despite adherence, or clinician concern about atypical features are often documented in free text rather than structured fields. NLP-enabled AI systems can extract these signals and incorporate them into predictive frameworks, enhancing diagnostic sensitivity without requiring additional clinician input.[133]

Despite encouraging results, several challenges limit the widespread adoption of AI for secondary hypertension detection. Prevalence is low for many secondary causes, creating a class imbalance that complicates model training and evaluation. False positives may increase downstream testing and health care costs if models are not carefully calibrated; furthermore, diagnostic labels used for training are often incomplete or inaccurate, reflecting real-world underdiagnosis rather than the true absence of disease.[134] These factors necessitate cautious interpretation of model outputs and reinforce the importance of human oversight.

Clinical integration is another major consideration. AI-based alerts identifying patients at risk for secondary hypertension must be presented in a manner that supports clinician workflow and decision-making (Figure). Systems that generate frequent or nonspecific alerts risk contributing to alert fatigue, undermining their intended benefit.[12] Successful implementation will likely require integration with clinical pathways that specify recommended next steps, such as targeted laboratory testing or referral to specialists.

Access to diagnostic testing for secondary hypertension varies widely across health care systems and populations. AI tools that preferentially identify patients already engaged in care or with extensive laboratory testing may inadvertently widen disparities. Ensuring that AI-driven screening approaches are applied equitably will require careful attention to data representativeness and implementation context.[135]

Thus, AI offers a powerful means to improve the detection of secondary hypertension by synthesizing complex clinical information and highlighting patients who warrant targeted evaluation. Although early studies demonstrate promising diagnostic performance, translation into routine practice will depend on robust validation, thoughtful integration into clinical workflows, and attention to ethical and equity considerations. When appropriately implemented, AI-driven approaches have the potential to substantially reduce underdiagnosis and improve outcomes in this high-impact subgroup of patients.

AI-ENABLED BEHAVIORAL, ADHERENCE, AND THERAPEUTIC INTERVENTIONS IN HYPERTENSION

Behavioral factors and medication adherence are among the most important yet least reliably addressed determinants of BP control. Lifestyle behaviors, such as diet, physical activity, alcohol consumption, sleep, and stress, profoundly influence BP regulation, while long-term adherence to antihypertensive therapy remains suboptimal across health care systems. AI offers new opportunities to address these challenges by enabling personalized, adaptive interventions that respond to individual behavior patterns and treatment responses over time.

AI-driven digital health interventions have been developed to support lifestyle modification in individuals with or at risk for hypertension.[136] These systems often integrate data from smartphones, wearables, and self-reported inputs to deliver tailored feedback, reminders, and educational content.[137]

ML algorithms can adapt intervention strategies based on user engagement, behavioral responses, and physiological signals, thereby moving beyond static educational programs. For example, smartphone-based hypertension management platforms have used reinforcement learning models to adjust the timing and frequency of medication reminders according to individual adherence patterns, reducing notification fatigue while maintaining engagement.[138,139] Similarly, remote BP monitoring programs integrated within health systems have deployed ML models embedded in EHRs to identify patients at risk of persistent uncontrolled BP and dynamically tailor outreach intensity (escalating from automated messages to pharmacist or nurse-led teleconsultations when home

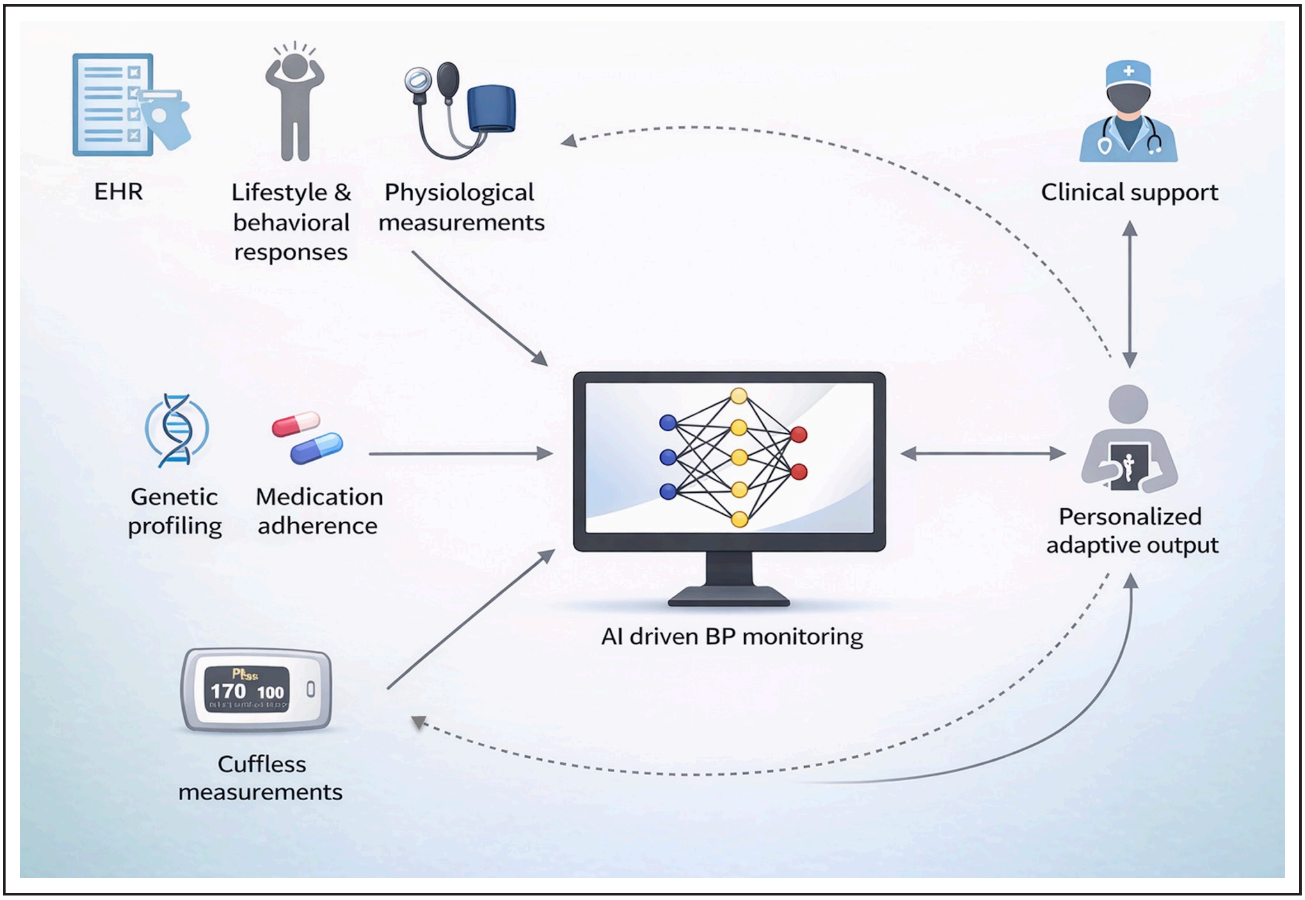

Figure. Workflow diagram illustrating how an artificial intelligence (AI)-enhanced intervention in hypertension operates.
BP indicates blood pressure; and EHR, electronic health records.

BP trends fail to improve).[140,141] Wearable-enabled interventions have also incorporated algorithms that analyze activity levels, sleep patterns, and heart rate variability to personalize lifestyle prompts, such as recommending brief walking sessions after detecting prolonged sedentary behavior or stress-related physiological changes associated with BP elevation.[142,143] AI-enhanced approaches may achieve modest but clinically meaningful reductions in systolic BP, particularly when combined with human support, as hybrid models allow clinicians to contextualize algorithm-driven adjustments and reinforce behavioral change.[144]

Medication adherence represents a critical target for AI-based interventions. Nonadherence contributes substantially to apparent treatment resistance and poor BP control, yet it is difficult to detect using routine clinical data.[145–150] AI models trained on prescription refill patterns, visit frequency, and longitudinal BP trends have been shown to identify patients at high risk for nonadherence. By distinguishing likely nonadherence from true pharmacological resistance, these models can inform more appropriate clinical responses, such as adherence counseling rather than medication escalation.[151] Conversational agents and chatbot-based interventions represent a growing area of interest in hypertension management. These systems use NLP to interact with patients, provide education, reinforce adherence, and support self-management behaviors.[152–154] Randomized trials evaluating conversational agents for hypertension have reported improvements in medication adherence and patient engagement, although effects on BP reduction have been variable.[155,156] These findings suggest that AI-driven communication tools may be most effective as adjuncts to, rather than replacements for, clinician-led care.[157]

AI has also been applied to optimize antihypertensive therapy selection and titration. Traditional treatment algorithms are largely guideline-driven and population-based, offering limited personalization beyond broad comorbidity categories. AI models trained on clinical trials and real-world data have been used to predict individual responses to specific drug classes, estimate the risk of adverse effects, and simulate alternative treatment strategies. Such approaches aim to identify the most effective therapy for a given patient while minimizing trial-and-error prescribing.

Decision support systems incorporating AI-generated recommendations have shown promise in improving BP control when integrated into clinical workflows. Systems that provide patient-specific treatment suggestions, highlight uncontrolled BP patterns, or prompt timely medication intensification have been associated with improved guideline adherence and BP outcomes in some studies. However, success depends heavily on clinician trust, interpretability of recommendations, and alignment with existing care processes.[158] Despite these advances, several limitations constrain the current impact of AI-enabled behavioral and therapeutic interventions. Engagement with digital tools often declines over time, reducing long-term effectiveness. Many studies are of short duration and involve motivated participants, limiting generalizability. Additionally, AI systems that rely heavily on patient-generated data may exclude individuals with limited digital access or literacy, raising concerns about equity and scalability.[159]

Ethical considerations are particularly salient in this domain. Behavioral interventions powered by AI may influence patient choices in subtle ways, raising questions about autonomy, transparency, and informed consent. Furthermore, the use of predictive models to identify nonadherence must be handled sensitively to avoid stigmatization or erosion of trust. Ethical frameworks for AI in cardiovascular care emphasize the importance of shared decision-making and clinician oversight when deploying such tools.[160] AI–enabled interventions targeting behavior, adherence, and therapeutic decision-making hold significant promise for improving BP control. By personalizing interventions, detecting barriers to adherence, and supporting more precise treatment selection, AI can address key drivers of uncontrolled hypertension. Realizing this potential will require sustained engagement strategies, rigorous evaluation, and careful integration into patient-centered care models.

MULTI-OMICS, GENOMICS, AND PRECISION HYPERTENSION ENABLED BY AI

Hypertension is a biologically heterogeneous disorder arising from complex interactions among genetic susceptibility, molecular pathways, environmental exposures, and behavioral factors. Traditional clinical classifications based on BP thresholds fail to capture this underlying diversity, contributing to variable treatment responses and inconsistent outcomes. AI has emerged as a powerful tool for integrating multi-omics data and uncovering biological mechanisms that may enable a transition from population-based hypertension management toward precision medicine.

Genome-wide association studies have identified hundreds of genetic loci associated with BP regulation, yet the individual effect sizes of most variants are small, limiting their clinical utility when considered in isolation. AI-based approaches, including ML and deep learning, have been applied to large-scale genomic data sets to model complex gene–gene and gene–environment interactions that influence hypertension risk.[161] Polygenic risk scores derived using advanced computational methods have demonstrated improved prediction of incident hypertension compared with traditional genetic risk models, particularly when combined with clinical and lifestyle factors.[162] Transcriptomics, proteomics, and metabolomics offer complementary insights into the molecular processes underlying BP regulation. AI methods are particularly well-suited to these high-dimensional data sets, where traditional statistical techniques struggle with multicollinearity and noise. Integrative analyses using ML have identified molecular signatures associated with salt sensitivity, vascular remodeling, and neurohormonal activation, providing potential targets for novel therapeutic interventions.[163–170] These studies illustrate how AI can facilitate hypothesis generation and accelerate biological discovery in hypertension research.

Single-cell and spatial omics technologies have further expanded the scope of precision hypertension research by enabling cell-type–specific analysis of gene expression in vascular, renal, and cardiac tissues. AI-driven clustering and pattern recognition methods have been used to identify distinct cellular states and regulatory networks implicated in BP control.[165] These approaches have revealed previously unrecognized roles for specific vascular smooth muscle cell phenotypes and renal tubular cell populations in hypertension pathogenesis.

AI has also been applied to link genetic variation with pharmacological response, an area of particular relevance for antihypertensive therapy.[8,159] Pharmacogenomic studies using ML have explored associations between genetic profiles and response to drug classes such as beta-blockers, renin–angiotensin system inhibitors, and calcium channel blockers.[171–175] Although results remain preliminary, these studies suggest that AI-guided pharmacogenomics could eventually inform individualized drug selection and dosing strategies in hypertension.

Despite rapid advances, significant barriers remain to the clinical translation of AI-enabled precision hypertension. Most omics studies are conducted in research cohorts that lack phenotypic depth, longitudinal follow-up, or ethnic diversity.[176,177] The integration of multi-omics data with clinical information is computationally and methodologically complex, and reproducibility across cohorts remains a concern. Furthermore, the incremental predictive value of omics-informed AI models over conventional clinical models is often modest, raising questions about cost-effectiveness and scalability.[178]

Genetic and omics data sets disproportionately represent individuals of European ancestry, which may limit the applicability of AI-driven precision tools in more diverse populations.[179,180] Without deliberate efforts to broaden representation, precision hypertension approaches risk exacerbating existing disparities in cardiovascular care. Ethical frameworks emphasize the need for transparency, equitable data inclusion, and patient engagement in the development and deployment of genomics-informed AI systems.[181]

AI has substantially expanded the analytical capacity required to integrate multi-omics data and unravel the biological complexity of hypertension. By enabling the discovery of molecular pathways, genetic risk profiles, and potential therapeutic targets, AI supports the vision of precision hypertension.[182] However, translation into routine clinical practice will require rigorous validation, diverse population representation, and a clear demonstration of clinical utility beyond existing risk assessment and treatment paradigms.

CLINICAL DECISION SUPPORT, ETHICS, EQUITY, AND IMPLEMENTATION CHALLENGES IN AI-DRIVEN HYPERTENSION CARE

The ultimate clinical value of AI in hypertension depends on its successful integration into decision-making processes that improve patient outcomes without increasing burden, bias, or inequity (Table 3). Clinical decision support systems represent the primary interface through which AI insights are translated into action, yet their effectiveness hinges on thoughtful design, transparency, and alignment with real-world workflows.[183,184] In hypertension care, where management decisions are frequent, longitudinal, and context-dependent, poorly implemented AI tools risk exacerbating alert fatigue, clinician skepticism, and unintended harm.

AI-driven clinical decision support systems in hypertension have been designed to assist with tasks such as identifying uncontrolled BP, recommending treatment intensification, prioritizing high-risk patients, and supporting adherence monitoring.[136] Decision support seems to be most effective when it delivers concise, patient-specific recommendations rather than abstract risk scores or probabilistic outputs.[185,186] Clinician trust is strongly influenced by interpretability and perceived clinical relevance, underscoring the importance of explainable AI approaches in this domain. Human-in-the-loop models are increasingly viewed as essential for the responsible deployment of AI in hypertension management.[187] Rather than replacing clinical judgment, AI systems are most effective when they augment clinician expertise by highlighting patterns, risks, or options that may not be readily apparent. This collaborative paradigm allows clinicians to contextualize AI recommendations within the broader clinical picture, incorporating patient preferences, comorbidities, and social factors that may not be fully captured by algorithms.

Ethical considerations permeate every stage of AI development and deployment in hypertension care; data privacy is a central concern, particularly as AI systems increasingly rely on continuous monitoring, wearable devices, and patient-generated data collected outside traditional health care environments.[188,189] Transparent data governance, clear consent processes, and robust security measures are necessary to maintain patient trust and comply with regulatory standards.

Bias and fairness represent some of the most pressing ethical challenges. Hypertension disproportionately affects racial and ethnic minorities, older adults, and individuals of lower socioeconomic status.[28,190] AI models trained on nonrepresentative data sets may underperform or behave unpredictably in these populations, potentially reinforcing existing disparities in diagnosis and treatment. Multiple analyses have demonstrated that algorithmic performance can vary significantly across demographic subgroups unless explicitly addressed during model development and validation.[191,192]

Equity considerations extend beyond algorithmic bias to issues of access and implementation.[193] AI-enabled hypertension tools often depend on digital infrastructure, wearable devices, or frequent health care engagement, which may be less accessible to vulnerable populations. Without deliberate design and policy interventions, AI-driven care models risk benefiting already advantaged

Table 3. Ethical, Regulatory, and Equity Considerations in AI-Driven Hypertension Care.

Domain	Core issue	Potential risk	Evidence-based concern	Mitigation strategies
Data bias	Nonrepresentative training data sets	Reduced accuracy in minority populations	Documented performance variation across demographics	Diverse cohort inclusion; subgroup validation
Transparency	Black-box models	Loss of clinician trust	Limited interpretability impairs adoption	Explainable AI; clinician-in-the-loop systems
Privacy	Continuous data collection	Breach of patient confidentiality	Wearables and EHR linkage increase exposure risk	Robust governance; consent frameworks
Clinical responsibility	Algorithm-driven recommendations	Automation bias	Overreliance may impair judgment	Decision support rather than automation
Regulatory oversight	Adaptive learning systems	Inconsistent performance over time	Existing frameworks are not designed for evolving models	Postdeployment monitoring; version control
Health equity	Differential access to digital tools	Widening disparities	Unequal access to wearables and AI platforms	Hybrid care models; equity-focused evaluation

AI indicates artificial intelligence; and EHR, electronic health records.

groups while leaving others behind.[154] Equity-oriented frameworks advocate for inclusive data collection, community engagement, and evaluation of real-world impact across diverse settings. Regulatory and implementation challenges further complicate translation into routine practice.[194] Many AI systems evolve through continuous learning, raising questions about version control, reproducibility, and regulatory oversight.[195] Existing medical device frameworks are not fully adapted to adaptive algorithms, creating uncertainty for developers, clinicians, and health systems.[194] In hypertension care, where long-term safety and consistency are paramount, these challenges must be addressed before widespread deployment.

Implementation science perspectives highlight that technical performance alone does not guarantee clinical impact.[196] Successful integration of AI into hypertension care requires attention to clinician training, workflow redesign, reimbursement models, and organizational culture. Studies of digital health interventions consistently demonstrate that systems co-designed with clinicians and patients are more likely to be adopted and sustained.[197] Clinical decision support systems powered by AI have the potential to enhance hypertension management, but their success depends on ethical, equitable, and context-sensitive implementation.[26,198] Human oversight, transparency, bias mitigation, and alignment with clinical workflows are essential to ensure that AI serves as a tool for improving care rather than a source of unintended consequences.

Regulatory oversight of adaptive AI-based clinical decision support tools is rapidly evolving, particularly under frameworks developed by the US Food and Drug Administration for software as a medical device. Continuously learning algorithms challenge traditional premarket review models, which are based on static versions of devices, prompting consideration of lifecycle-based regulatory approaches that incorporate predefined change control plans, postmarket monitoring, and real-world performance surveillance.[199] Clear guidance on accountability, documentation of algorithm updates, and transparency in performance across subgroups will be essential to ensure safety and maintain clinician and public trust. In addition, clinician training and AI literacy represent critical, and often underestimated, determinants of successful implementation. Many clinicians receive limited formal education in data science, algorithmic bias, or model interpretability, which may hinder appropriate use or foster overreliance and skepticism. Structured educational initiatives, interdisciplinary collaboration, and integration of AI competencies into continuing medical education may help bridge this gap and promote responsible adoption.[200]

CONCLUSIONS

AI represents a powerful and rapidly evolving paradigm in hypertension research and clinical care. Across the continuum from risk prediction and early detection to phenotyping, treatment optimization, and long-term management, AI offers tools capable of integrating complex, longitudinal, and multimodal data in ways that surpass traditional analytical approaches. The literature reviewed herein demonstrates that AI tools can improve the prediction of incident hypertension, enhance detection of secondary causes, support personalized behavioral and pharmacological interventions, and deepen biological understanding through multi-omics integration.

At the same time, this body of evidence underscores that most AI applications in hypertension remain at an early stage of translation. Many models are retrospectively developed, inconsistently validated, and insufficiently evaluated in diverse real-world populations. BP measurement variability, data quality limitations, and challenges in workflow integration continue to constrain clinical impact. Importantly, the promise of AI will not be realized through algorithmic sophistication alone, but through rigorous validation, prospective evaluation, and thoughtful implementation grounded in clinical reality.

Ethical considerations, particularly those related to equity, transparency, and patient autonomy, must remain central as AI-driven hypertension care advances. Without deliberate efforts to address bias, representation, and access, AI risks perpetuating existing disparities in cardiovascular health. Conversely, when developed and deployed responsibly, AI has the potential to support more precise, proactive, and equitable hypertension care.

In conclusion, AI should be viewed not as a replacement for clinicians or established guidelines, but as an enabling technology that augments human judgment and supports data-informed decision-making. Continued interdisciplinary collaboration among clinicians, data scientists, ethicists, and policymakers will be essential to translate AI's promise into meaningful improvements in hypertension outcomes.

ARTICLE INFORMATION

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Sources of Funding

The Santulli Lab was supported in part by the American Heart Association (AHA; 24IPA1268813) and by the National Institutes of Health (NIH): National Heart, Lung, and Blood Institute (NHLBI: R01-HL164772, R01-HL159062, and R01-HL146691), National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK: R01-DK123259, R01-DK033823). F. Varzideh was supported in part by the AHA (POST915561 and POST1195524). U. Kansakar was supported in part by the NIH (T32-HL-172255) and by a postdoctoral fellowship of the AHA (POST1026190). S. Pande was supported in part by a postdoctoral fellowship of the AHA (POST1563063). S.S. Jankauskas was supported in part by a postdoctoral fellowship of the AHA (POST836407).

Disclosures

None.

REFERENCES

1. Liu F, Pan HW, Li YY, Zhao XJ, Hong XQ, Liu ZY, You YY. Trends analysis of the global burden of hypertensive heart disease from 1990 to 2021: a population-based study. *BMC Public Health*. 2025;25:2233. doi: 10.1186/s12889-025-23389-6
2. Forzano I, Mone P, Varzideh F, Jankauskas SS, Kansakar U, De Luca A, Santulli G. The selective aldosterone synthase inhibitor Baxdrostat significantly lowers blood pressure in patients with resistant hypertension. *Front Endocrinol*. 2022;13:1097968. doi: 10.3389/fendo.2022.1097968
3. Joyner MJ, Limberg JK. Blood pressure regulation: every adaptation is an integration? *Eur J Appl Physiol*. 2014;114:445–450. doi: 10.1007/s00421-013-2636-5
4. Jankauskas SS, Kansakar U, Mone P, Varzideh F, Santulli G. Like a rolling tone: ablating LRRC8A eases inflammation and keeps vessels moving. *Hypertension*. 2026;83:54–56. doi: 10.1161/HYPERTENSIONAHA.125.26261
5. Ramos E, Pilo Palax I, Serech Cuxil E, Sebaquijay Iquic E, Canu Ajqui A, Miller AC, Chandrasekeran S, Hall-Clifford R, Sameni R, Katebi N, et al. Mobil Monitoring Doppler Ultrasound (MoMDUS) study: protocol for a prospective, observational study investigating the use of artificial intelligence and low-cost Doppler ultrasound for the automated quantification of hypertension, pre-eclampsia and fetal growth restriction in rural Guatemala. *BMJ Open*. 2024;14:e090503. doi: 10.1136/bmjopen-2024-090503
6. Wang Y, Bai L, Yang J, Lu Y, Fan W, Nie Z, Yu J, Wen K, Wang R, He L, et al. Artificial intelligence measuring the aortic diameter assist in identifying adverse blood pressure status including masked hypertension. *Postgrad Med*. 2022;134:111–121. doi: 10.1080/00325481.2021.2003150
7. Hardacre CJ, Robertshaw JA, Barratt SL, Adams HL, MacKenzie Ross RV, Robinson GR, Suntharalingam J, Pauling JD, Rodrigues JCL. Diagnostic test accuracy of artificial intelligence analysis of cross-sectional imaging in pulmonary hypertension: a systematic literature review. *Br J Radiol*. 2021;94:20210332. doi: 10.1259/bjr.20210332
8. Dherani M, Wagner SK, Shantsila E. The role of artificial intelligence in hypertension management. *Curr Opin Nephrol Hypertens*. 2026;35:181–187. doi: 10.1097/MNH.0000000000001157
9. Suvila K, McCabe EL, Lehtonen A, Ebinger JE, Lima JAC, Cheng S, Niiranen TJ. Early onset hypertension is associated with hypertensive end-organ damage already by midLife. *Hypertension*. 2019;74:305–312. doi: 10.1161/HYPERTENSIONAHA.119.13069
10. Truong ATL, Tan SB, Wang GZ, Yip AWJ, Egermark M, Yeung W, Lee VV, Chan MY, Kumar KS, Tan LWJ, et al. CURATE.AI-assisted dose titration for anti-hypertensive personalized therapy: study protocol for a multi-arm, randomized, pilot feasibility trial using CURATE.AI (CURATE.AI ADAPT trial). *Eur Heart J Digit Health*. 2024;5:41–49. doi: 10.1093/ehjdh/ztad063
11. Layton AT. A heart-to-heart with ChatGPT: AI applications in hypertension. *Am J Hypertens*. 2025;38:621–627. doi: 10.1093/ajh/hpaf045
12. Alam SF, Thongprayoon C, Miao J, Pham JH, Sheikh MS, Garcia Valencia OA, Schwartz GL, Craici IM, Gonzalez Suarez ML, Cheungpasitporn W. Advancing personalized medicine in digital health: The role of artificial intelligence in enhancing clinical interpretation of 24-h ambulatory blood pressure monitoring. *Digit Health*. 2025;11:20552076251326014. doi: 10.1177/20552076251326014
13. Naik A, Nalepa J, Wijata AM, Mahon J, Mistry D, Knowles AT, Dawson EA, Lip GYH, Olier I, Ortega-Martorell S. Artificial intelligence and digital twins for the personalised prediction of hypertension risk. *Comput Biol Med*. 2025;196:110718. doi: 10.1016/j.compbiomed.2025.110718
14. Abrahamowicz AA, Ebinger J, Whelton SP, Commodore-Mensah Y, Yang E. Racial and ethnic disparities in hypertension: barriers and opportunities to improve blood pressure control. *Curr Cardiol Rep*. 2023;25:17–27. doi: 10.1007/s11886-022-01826-x
15. Sau A, Barker J, Pastika L, Sieliwonczyk E, Patlatzoglou K, McGurk KA, Peters NS, O'Regan DP, Ware JS, Kramer DB, et al. Artificial intelligence-enhanced electrocardiography for prediction of incident hypertension. *JAMA Cardiol*. 2025;10:214–223. doi: 10.1001/jamacardio.2024.4796
16. Garcia-Rudolph A, Sanchez-Pinsach D, Opisso E. Evaluation of domain-specific vs general purpose GPT models for SCI-related gastrointestinal, cardiovascular and pulmonary complications. *J Spinal Cord Med*. 2025;48:718–719. doi: 10.1080/10790268.2024.2420433
17. Han C, Kim DW, Kim S, Chan You S, Park JY, Bae S, Yoon D. Evaluation of GPT-4 for 10-year cardiovascular risk prediction: insights from the UK Biobank and KoGES data. *iScience*. 2024;27:109022. doi: 10.1016/j.isci.2024.109022
18. Dunn P, Ali A, Patel AP, Banerjee S. Brief review and primer of key terminology for artificial intelligence and machine learning in hypertension. *Hypertension*. 2025;82:26–35. doi: 10.1161/HYPERTENSIONAHA.123.22347
19. Silva GFS, Fagundes TP, Teixeira BC, Chiavegatto Filho ADP. Machine learning for hypertension prediction: a systematic review. *Curr Hypertens Rep*. 2022;24:523–533. doi: 10.1007/s11906-022-01212-6
20. Arevalo-Cordovilla FE, Pena M. Evaluating ensemble models for fair and interpretable prediction in higher education using multimodal data. *Sci Rep*. 2025;15:29420. doi: 10.1038/s41598-025-15388-9
21. Guimaraes P, Keller A, Bohm M, Lauder L, Fehlmann T, Ruilope LM, Vinyoles E, Gorostidi M, Segura J, Ruiz-Hurtado G, et al. Artificial intelligence-derived risk prediction: a novel risk calculator using office and ambulatory blood pressure. *Hypertension*. 2025;82:46–56. doi: 10.1161/HYPERTENSIONAHA.123.22529
22. Krittanawong C, Bomback AS, Baber U, Bangalore S, Messerli FH, Wilson Tang WH. Future direction for using artificial intelligence to predict and manage hypertension. *Curr Hypertens Rep*. 2018;20:75. doi: 10.1007/s11906-018-0875-x
23. Cross JL, Choma MA, Onofrey JA. Bias in medical AI: implications for clinical decision-making. *PLOS Digit Health*. 2024;3:e0000651. doi: 10.1371/journal.pdig.0000651
24. Zhou S, Xu Z, Zhang M, Xu C, Guo Y, Zhan Z, Fang Y, Ding S, Wang J, Xu K, et al. Large language models for disease diagnosis: a scoping review. *NPJ Artif Intell*. 2025;1:9. doi: 10.1038/s44387-025-00011-z
25. Kanegae H, Suzuki K, Fukatani K, Ito T, Harada N, Kario K. Highly precise risk prediction model for new-onset hypertension using artificial intelligence techniques. *J Clin Hypertens (Greenwich)*. 2020;22:445–450. doi: 10.1111/jch.13759
26. Fahim YA, Hasani IW, Kabba S, Ragab WM. Artificial intelligence in healthcare and medicine: clinical applications, therapeutic advances, and future perspectives. *Eur J Med Res*. 2025;30:848. doi: 10.1186/s40001-025-03196-w
27. Chaikijurajai T, Laffin LJ, Tang WHW. Artificial intelligence and hypertension: recent advances and future outlook. *Am J Hypertens*. 2020;33:967–974. doi: 10.1093/ajh/hpaa102
28. Amponsah D, Thamman R, Brandt E, James C, Spector-Bagdady K, Yong CM. Artificial intelligence to promote racial and ethnic cardiovascular health equity. *Curr Cardiovasc Risk Rep*. 2024;18:153–162. doi: 10.1007/s12170-024-00745-6
29. Armoundas AA, Ahmad FS, Attia ZI, Doudesis D, Khera R, Kyriakoulis KG, Stergiou GS, Tang WHW. Controversy in hypertension: pro-side of the argument using artificial intelligence for hypertension diagnosis and management. *Hypertension*. 2025;82:929–944. doi: 10.1161/HYPERTENSIONAHA.124.22349
30. Sekitoleko I, Byrd JB. Controversy in hypertension: con-side of the argument using AI for HTN diagnosis and management. *Hypertension*. 2025;82:1789–1793. doi: 10.1161/HYPERTENSIONAHA.125.23626
31. Naing P, Scalia GM, Murdoch D, Ranasinghe I, Forrester DL, Strange G, Playford D. Artificial intelligence enhanced contemporary pulmonary hypertension care. *Am Heart J Plus*. 2025;60:100673. doi: 10.1016/j.ahjo.2025.100673
32. White RD, Demirer M, Sebro RA, Cortopassi IO, Stowell JT, McCann MR, Barry T, Appleton CP, Helgeson SA, Erdal BS. Artificial intelligence improves detection and classification of pulmonary venous hypertension related to left ventricular diastolic dysfunction by chest radiography. *Sci Rep*. 2025;15:38181. doi: 10.1038/s41598-025-22026-x
33. Kramer T, Kramer M, Hagist C, Spinler S. Artificial intelligence in pulmonary hypertension: a systematic review. *Eur J Med Res*. 2025;30:1225. doi: 10.1186/s40001-025-03557-5
34. Salehi M, Alabed S, Sharkey M, Maiter A, Dwivedi K, Yardibi T, Selej M, Hameed A, Charalampopoulos A, Kiely DG, et al. Artificial intelligence-based echocardiography assessment to detect pulmonary hypertension. *ERJ Open Res*. 2024;11:00592–02024. doi: 10.1183/23120541.00592-2024
35. Celestin B, Bagherzadeh SP, Santana E, Frost M, Iversen M, Hermansson FN, Sweatt A, Zamanian RT, Hummel YM, Rendon GG, et al. Artificial intelligence-based echocardiography in pulmonary arterial hypertension. *Chest*. 2026;169:207–219. doi: 10.1016/j.chest.2025.06.052
36. Zeng Y, Ling G, Zhang H, Cao W, Zheng X, Deng X, Lan L, Sun R, Liu X, Tian L, et al. Artificial intelligence-driven multivariate integration for pulmonary arterial pressure prediction in pulmonary hypertension. *NPJ Digit. Med*. 2025;9:56. doi: 10.1038/s41746-025-02233-6
37. Xu W, Xi L, Ni Y, Wang J, Yang H, Liu A, Gao Q, Tao X, Huang Q, Liu X, et al. Artificial intelligence-driven quantitative analysis of CT morphological differences between chronic thromboembolic pulmonary hypertension and chronic thromboembolic disease. *Quant Imaging Med Surg*. 2025;15:1101–1113. doi: 10.21037/qims-24-1301
38. Ahmed F, Haider F, Arham M, Dad A, Bakht K, Hashim MMA, Lajczak P, Hassan M, Athar FB, Adnan M, et al. Comparative diagnostic accuracy of artificial intelligence-derived risk stratification versus conventional risk stratification methods in pulmonary hypertension patients: a

systematic review and meta-analysis. *Front Artif Intell*. 2025;8:1692829. doi: 10.3389/frai.2025.1692829

39. Attaripour Esfahani S, Baba Ali N, Farina JM, Scalia IG, Pereyra M, Abbas MT, Javadi N, Bismee NN, Abdelfattah FE, Awad K, et al. A comprehensive review of artificial intelligence applications in pulmonary hypertension. *Medicina (Kaunas)*. 2025;61:85. doi: 10.3390/medicina61010085
40. Jain S, Kaur A, Qadeer A, Ghosh V, Thota S, Banala M, Lee J, Yerrapragada G, Elangovan P, Shariff MN, et al. Leveraging artificial intelligence for the diagnosis of systemic sclerosis associated pulmonary arterial hypertension: opportunities, challenges, and future perspectives. *Adv Respir Med*. 2025;93:47. doi: 10.3390/arm93050047
41. Ledzinski L, Grzesk G, Ziolkowski M, Waligora M, Kurzyna M, Mularek-Kubzdela T, Smukowska-Gorynia A, Skoczylas I, Chrzanowski L, Blaszczak P, et al. Personalized medicine in pulmonary arterial hypertension: utilizing artificial intelligence for death prevention. *J Clin Med*. 2025;14:8325. doi: 10.3390/jcm14238325
42. Benesch Vidal ML, Arvanitaki A, Diller GP. The role of artificial intelligence and mobile health in diagnosis and management of pulmonary arterial hypertension. *Int J Cardiol Congenit Heart Dis*. 2025;22:100622. doi: 10.1016/j.ijcchd.2025.100622
43. Khamissi FZ, Sun L, Johnson P, Shah S, Benjamin IJ. Machine learning and artificial intelligence for research on hypertension. *Am J Hypertens*. 2025;38:867–871. doi: 10.1093/ajh/hpaf051
44. Hirata Y, Tsuji T, Kotoku J, Sata M, Kusunose K. Echocardiographic artificial intelligence for pulmonary hypertension classification. *Heart*. 2024;110:586–593. doi: 10.1136/heartjnl-2023-323320
45. Kheyfets VO, Sweatt AJ, Gomberg-Maitland M, Ivy DD, Condliffe R, Kiely DG, Lawrie A, Maron BA, Zamanian RT, Stenmark KR. Computational platform for doctor-artificial intelligence cooperation in pulmonary arterial hypertension prognostication: a pilot study. *ERJ Open Res*. 2023;9:00484–02022. doi: 10.1183/23120541.00484-2022
46. Tu S, Chu M. The match of electrocardiogram and artificial intelligence confers an opportunity for pulmonary hypertension screening. *JACC Asia*. 2022;2:271–272. doi: 10.1016/j.jacasi.2022.03.006
47. Fortmeier V, Lachmann M, Korber MI, Unterhuber M, von Scheidt M, Rippen E, Harmsen G, Gercek M, Friedrichs KP, Roder F, et al. Solving the pulmonary hypertension paradox in patients with severe tricuspid regurgitation by employing artificial intelligence. *JACC Cardiovasc Interv*. 2022;15:381–394. doi: 10.1016/j.jcin.2021.12.043
48. Kwon JM, Kim KH, Medina-Inojosa J, Jeon KH, Park J, Oh BH. Artificial intelligence for early prediction of pulmonary hypertension using electrocardiography. *J Heart Lung Transplant*. 2020;39:805–814. doi: 10.1016/j.healun.2020.04.009
49. Kiely DG, Doyle O, Drage E, Jenner H, Salvatelli V, Daniels FA, Rigg J, Schmitt C, Samyshkin Y, Lawrie A, et al. Utilising artificial intelligence to determine patients at risk of a rare disease: idiopathic pulmonary arterial hypertension. *Pulm Circ*. 2019;9:2045894019890549. doi: 10.1177/2045894019890549
50. Wang QC, Jiao J, Zhang CQ. Application of artificial intelligence in portal hypertension and esophagogastric varices. *World J Gastroenterol*. 2025;31:108508. doi: 10.3748/wjg.v31.i24.108508
51. He Y, Gao Q, Mo S, Huang K, Liao Y, Liang T, Chen M, Wang J, Tao Q, Zhang G, et al. Artificial intelligence algorithm was used to establish and verify the prediction model of portal hypertension in hepatocellular carcinoma based on clinical parameters and imaging features. *J Gastrointest Oncol*. 2025;16:159–175. doi: 10.21037/jgo-2024-931
52. Khooblall A, Viswanath SE, Khawaja L, Gadani S. Artificial intelligence applications in the diagnosis and management of cirrhosis and portal hypertension: a narrative review. *Tech Vasc Interv Radiol*. 2025;28:101078. doi: 10.1016/j.tvir.2025.101078
53. Yu Q, Huang Y, Li X, Pavlides M, Liu D, Luo H, Ding H, An W, Liu F, Zuo C, et al. An imaging-based artificial intelligence model for non-invasive grading of hepatic venous pressure gradient in cirrhotic portal hypertension. *Cell Rep Med*. 2022;3:100563. doi: 10.1016/j.xcrm.2022.100563
54. Li X, Kang N, Qi X, Huang Y. Artificial intelligence in the diagnosis of cirrhosis and portal hypertension. *J Med Ultrason (2001)*. 2022;49:371–379. doi: 10.1007/s10396-021-01153-8
55. Giles TD, Sander GE. The new International Classification of Diseases (ICD-10): the hypertension community needs a greater input. *J Clin Hypertens (Greenwich)*. 2012;14:1–2. doi: 10.1111/j.1751-7176.2011.00546.x
56. Valvi N, McFarlane T, Allen KS, Gibson PJ, Dixon BE. Identification of hypertension in electronic health records through computable phenotype development and validation for use in public health surveillance: retrospective study. *JMIR Form Res*. 2023;7:e46413. doi: 10.2196/46413
57. Falter M, Godderis D, Scherrenberg M, Kizilkilic SE, Xu L, Mertens M, Jansen J, Legroux P, Kindermans H, Sinnaeve P, et al. Using natural language processing for automated classification of disease and to identify misclassified ICD codes in cardiac disease. *Eur Heart J Digit Health*. 2024;5:229–234. doi: 10.1093/ehjdh/ztae008
58. Kenger EB, Karahan TO. Artificial intelligence-generated diet plans for hypertension and dyslipidemia: adherence and nutritional insights. *Iran J Public Health*. 2025;54:1243–1251. doi: 10.18502/ijph.v54i6.18902
59. Li L, Momma H, Chen H, Nawrin SS, Xu Y, Inada H, Nagatomi R. Dietary patterns associated with the incidence of hypertension among adult Japanese males: application of machine learning to a cohort study. *Eur J Nutr*. 2024;63:1293–1314. doi: 10.1007/s00394-024-03342-w
60. Chiu CC, Wu CM, Chien TN, Kao LJ, Li C, Chu CM. Integrating structured and unstructured EHR data for predicting mortality by machine learning and latent dirichlet allocation method. *Int J Environ Res Public Health*. 2023;20:4340. doi: 10.3390/ijerph20054340
61. Zhang D, Yin C, Zeng J, Yuan X, Zhang P. Combining structured and unstructured data for predictive models: a deep learning approach. *BMC Med Inform Decis Mak*. 2020;20:280. doi: 10.1186/s12911-020-01297-6
62. Wang Y, Tan W, Cheng S, Peng C, Peng J, Qin F, Tang L, Zhu T, Wu B, Liu J, et al. Large language model agent for managing patients with suspected hypertension. *Hypertension*. 2026;83:212–224. doi: 10.1161/HYPERTENSIONAHA.125.25305
63. Ning Y, Ong JCL, Cheng H, Wang H, Ting DSW, Tham YC, Wong TY, Liu N. How can artificial intelligence transform the training of medical students and physicians? *Lancet Digit Health*. 2025;7:100900. doi: 10.1016/j.landig.2025.100900
64. Zand J, Miao J, Hommos MS, Schwartz GL, Taler SJ, Nejat P, Cheungpasitporn W, Garovic VD, Zoghby ZM. Performance of large language models in analyzing common hypertension scenarios. *Hypertension*. 2026;83:225–234. doi: 10.1161/HYPERTENSIONAHA.125.25492
65. Wang Y, Luan Y, Cheng S, Hao M, Tan W, Hu R, Yao Z, Wang J, Wu J. A multilayer retrieval-augmented large language model framework for enhancing hypertension education. *Hypertens Res*. 2026;49:1428–1440. doi: 10.1038/s41440-025-02481-9
66. Yang H, Fan C, Liu C. Development and validation of a machine learning model to predict comorbid hypertension in patients with type 2 diabetes. *Front Med (Lausanne)*. 2026;13:1754916. doi: 10.3389/fmed.2026.1754916
67. Guimbaud JB, Calabre E, de Cid R, Lassale C, Kogevinas M, Maitre L, Cazabet R. An informed machine learning based environmental risk score for hypertension in European adults. *Artif Intell Med*. 2025;165:103139. doi: 10.1016/j.artmed.2025.103139
68. Yin C, Sun X, Dai A, Ye XY, Lu Y, Wang W, Chen Y, Jiang H, Yu J, Chong S, et al. ChatGPT in precision medicine. *APL Bioeng*. 2026;10:011502. doi: 10.1063/5.0299327
69. Moell B, Sand Aronsson F. Harm reduction strategies for thoughtful use of large language models in the medical domain: perspectives for patients and clinicians. *J Med Internet Res*. 2025;27:e75849. doi: 10.2196/75849
70. Aguzzi G, Magnini M, Farahmand A, Ferretti S, Pengo MF, Montagna S. RAG-enhanced open SLMs for hypertension management chatbots. *J Med Syst*. 2025;49:159. doi: 10.1007/s10916-025-02297-7
71. Shimbo D, Shah RU, Abdalla M, Agarwal R, Ahmad FS, Anaya G, Attia ZI, Bull S, Chang AR, Commodore-Mensah Y, et al. Transforming hypertension diagnosis and management in the era of artificial intelligence: a 2023 National Heart, Lung, and Blood Institute (NHLBI) workshop report. *Hypertension*. 2025;82:36–45. doi: 10.1161/HYPERTENSIONAHA.124.22095
72. Ghuman N, Campbell P, White WB. Role of ambulatory and home blood pressure recording in clinical practice. *Curr Cardiol Rep*. 2009;11:414–421. doi: 10.1007/s11886-009-0060-6
73. Hossain A, Townsend RR, Cohen JB. An updated meta-analysis of white coat hypertension and mortality. *J Hum Hypertens*. 2025;39:595–597. doi: 10.1038/s41371-025-01041-5
74. Kim HJ, Lee Y, Shin JH, Kim JH, Hwang SH, Kim WS, Park S, Rhee SJ, Lee EM, Ihm SH, et al. Impact of clinic blood pressure target on the prevalence and predictors of masked uncontrolled hypertension and white-coat uncontrolled hypertension. *J Korean Med Sci*. 2025;40:e117. doi: 10.3346/jkms.2025.40.e117
75. de la Sierra A, Ruilope LM, Staplin N, Stergiou GS, Vinyoles E, Williams B. Mortality risks in different subtypes of white-coat hypertension: implications for the diagnosis of white-coat hypertension. *J Hypertens*. 2025;43:1450–1456. doi: 10.1097/HJH.0000000000004076
76. Tran TQB, Lip S, du Toit C, Kalaria TK, Bhaskar RK, O'Neil AQ, Graff B, Hoffmann M, Szyndler A, Polonis K, et al. Assessing machine learning for diagnostic classification of hypertension types identified by

ambulatory blood pressure monitoring. *CJC Open*. 2024;6:798–804. doi: 10.1016/j.cjco.2024.03.005

77. Sun Q, Tian J, Zhang Z, Zhang L, Li J, Zhang L, Liang N, Huang K, Zhao Y. Validation of latent health behavior subtypes in young and middle-aged adults with hypertension: a machine learning-augmented LCA approach with external cohort replication. *Eur J Cardiovasc Nurs*. 2026-:zvag001. doi: 10.1093/eurjcn/zvag001
78. Yang E, Schutte AE, Stergiou G, Wyss FS, Commodore-Mensah Y, Odili A, Kronish I, Lee HY, Shimbo D. Cuffless blood pressure measurement devices-international perspectives on accuracy and clinical use: a narrative review. *JAMA Cardiol*. 2025;10:624–631. doi: 10.1001/jamacardio.2025.0662
79. Zhang Y, Qiu S, Du K, Wu S, Xiang T, Zheng K, Liu Z, Chen H, Ji N, Wang F, et al. Artificial intelligence-enhanced wearable blood pressure monitoring in resource-limited settings: a co-design of sensors, model, and deployment. *Nanomicro Lett*. 2026;18:164. doi: 10.1007/s40820-025-02003-9
80. Henry B, Merz M, Hoang H, Abdulkarim G, Wosik J, Schoettker P. Cuffless Blood Pressure in clinical practice: challenges, opportunities and current limits. *Blood Press*. 2024;33:2304190. doi: 10.1080/08037051.2024.2304190
81. Hu JR, Martin G, Iyengar S, Kovell LC, Plante TB, Helmond NV, Dart RA, Brady TM, Turkson-Ocran RN, Juraschek SP. Validating cuffless continuous blood pressure monitoring devices. *Cardiovasc Digit Health J*. 2023;4:9–20. doi: 10.1016/j.cvdhj.2023.01.001
82. Li Z, He B, Li Y, Liu BF, Zhang G, Liu S, Hu TY, Li Y. Synergizing nanosensor-enhanced wearable devices with machine learning for precision health management benefiting older adult populations. *ACS Nano*. 2025;19:26273–26295. doi: 10.1021/acsnano.5c04337
83. Kundrick J, Naniwadekar A, Singla V, Kancharla K, Bhonsale A, Voigt A, Shalaby A, Estes NAM, Jain SK, Saba S. Machine learning applied to wearable fitness tracker data and the risk of hospitalizations and cardiovascular events. *Am J Prev Cardiol*. 2025;22:101006. doi: 10.1016/j.ajpc.2025.101006
84. Khalil RM, Shulman LM, Gruber-Baldini AL, Reich SG, Savitt JM, Hausdorff JM, Coelln RV, Cummings MP. Applying wearable sensors and machine learning to the diagnostic challenge of distinguishing parkinson's disease from other forms of Parkinsonism. *Biomedicines*. 2025;13:572. doi: 10.3390/biomedicines13030572
85. Hadid A, McDonald EG, Ding Q, Phillipp C, Trottier A, Dixon PC, Jlassi O, Cheng MP, Papenburg J, Libman M, et al. Development of machine learning prediction models for systemic inflammatory response following controlled exposure to a live attenuated influenza vaccine in healthy adults using multimodal wearable biosensors in Canada: a single-centre, prospective controlled trial. *Lancet Digit Health*. 2025;7:100886. doi: 10.1016/j.landig.2025.100886
86. Liu T, Zhang M, Li Z, Dou H, Zhang W, Yang J, Wu P, Li D, Mu X. Machine learning-assisted wearable sensing systems for speech recognition and interaction. *Nat Commun*. 2025;16:2363. doi: 10.1038/s41467-025-57629-5
87. Min S, An J, Lee JH, Kim JH, Joe DJ, Eom SH, Yoo CD, Ahn HS, Hwang JY, Xu S, et al. Wearable blood pressure sensors for cardiovascular monitoring and machine learning algorithms for blood pressure estimation. *Nat Rev Cardiol*. 2025;22:629–648. doi: 10.1038/s41569-025-01127-0
88. Li A, Lian J, Vardhanabhuti V. Multi-modal machine learning approach for early detection of neurodegenerative diseases leveraging brain MRI and wearable sensor data. *PLOS Digit Health*. 2025;4:e0000795. doi: 10.1371/journal.pdig.0000795
89. Sheridan D, Jaspers A, Viet Cuong D, Op De Beeck T, Moyna NM, de Beukelaar TT, Roantree M. Estimating oxygen uptake in simulated team sports using machine learning models and wearable sensor data: a pilot study. *PLoS One*. 2025;20:e0319760. doi: 10.1371/journal.pone.0319760
90. Jiang Q, Zhao X, Zhao T, Li W, Ye J, Dong X, Wang X, Liu Q, Ding H, Ye Z, et al. A machine-learning-powered spectral-dominant multimodal soft wearable system for long-term and early-stage diagnosis of plant stresses. *Sci Adv*. 2025;11:eadw7279. doi: 10.1126/sciadv.adw7279
91. Peigan P, Ghomi F, Soltani S, Marques-Vidal P, Shabestari M, Namayandeh SM, Sarebanhassanabadi M. Which of the five anthropometric and lipid-based indexes best predicts hypertension? A machine learning approach. *Intern Emerg Med*. 2026. doi: 10.1007/s11739-026-04302-4
92. Sheikh AB, Sobotka PA, Garg I, Dunn JP, Minhas AMK, Shandhi MMH, Molinger J, McDonnell BJ, Fudim M. Blood pressure variability in clinical practice: past, present and the future. *J Am Heart Assoc*. 2023;12:e029297. doi: 10.1161/JAHA.122.029297
93. Squirrell DM, Yang S, Xie L, Ang S, Moghadam M, Vaghefi E, McConnell MV. Blood pressure predicted from artificial intelligence analysis of retinal images correlates with future cardiovascular events. *JACC Adv*. 2024;3:101410. doi: 10.1016/j.jacadv.2024.101410
94. Hathaway QA, Yanamala N, Sengupta PP. Multimodal data for systolic and diastolic blood pressure prediction: The hypertension conscious artificial intelligence. *EBioMedicine*. 2022;84:104261. doi: 10.1016/j.ebiom.2022.104261
95. Martinez-Garcia M, Gutierrez-Esparza GO, Marquez MF, Amezcua-Guerra LM, Hernandez-Lemus E. Machine learning analysis of emerging risk factors for early-onset hypertension in the Tlalpan 2020 cohort. *Front Cardiovasc Med*. 2024;11:1434418. doi: 10.3389/fcvm.2024.1434418
96. Miller B, Coeyman SJ, Wentzel A, Mels CMC, Richardson WJ. Machine learning model for detecting masked hypertension in young adults. *Front Physiol*. 2025;16:1684693. doi: 10.3389/fphys.2025.1684693
97. Lei J, Wu H, Liu H, Poon LC, Wang CC, Cai R, Su D, Jia J, Zou X, Yang H, et al. DNA methylation markers for pregnancy hypertension via machine learning methods. *Hypertension*. 2026;83:e25388. doi: 10.1161/HYPERTENSIONAHA.125.25388
98. Mirzaye AW, Saadatfar H, Nematollahi MA, Banerjee B. Enhancing hypertension risk diagnosis using a hybrid machine learning framework: leveraging body composition data. *Biomed Res Int*. 2026;2026:6335947. doi: 10.1155/bmri/6335947
99. Sood A, Gupta S, Borkar SR, Podder A, Jani P. Use of machine learning to predict hypertension based on BMI and routine lab data. *Bioinformation*. 2025;21:3645–3648. doi: 10.6026/973206300213645
100. Prabhakar SK, Won DO. Pragmatic models for detection of hypertension using ballistocardiograph signals and machine learning. *Bioengineering (Basel)*. 2025;13:43. doi: 10.3390/bioengineering13010043
101. Angelaki E, Kopidakis I, Barmparis GD, Fragkiadakis K, Maragkoudakis S, Kalomoirakis P, Kallergis E, Zacharis E, Kampanieris E, Alifragki A, et al. Single-lead ECG-based machine learning model for non-invasive detection of left ventricular hypertrophy in hypertension. *Hellenic J Cardiol*. 2026;S1109–9666(26)00004. doi: 10.1016/j.hjc.2026.01.004
102. Badr J, Motulsky A, Denis JL. Digital health technologies and inequalities: a scoping review of potential impacts and policy recommendations. *Health Policy*. 2024;146:105122. doi: 10.1016/j.healthpol.2024.105122
103. Katz ME, Mszar R, Grimshaw AA, Gunderson CG, Onuma OK, Lu Y, Spatz ES. Digital health interventions for hypertension management in US populations experiencing health disparities: a systematic review and meta-analysis. *JAMA Netw Open*. 2024;7:e2356070. doi: 10.1001/jamanetworkopen.2023.56070
104. Jankauskas SS, Varzideh F, Kansakar U, Santulli G. Artificial intelligence in cardiovascular medicine: a giant step in personalized medicine? *J Pers Med*. 2026. In press
105. Septian E, Khaefi MR, Athoillah A, Aisyah DN, Hardhantyo M, Rahman FM, Manikam L. Prediction of personalised hypertension using machine learning in indonesian population. *J Med Syst*. 2025;49:137. doi: 10.1007/s10916-025-02253-5
106. Zhang Y, Kreif N, Gc VS, Manca A. Machine learning methods to estimate individualized treatment effects for use in health technology assessment. *Med Decis Making*. 2024;44:756–769. doi: 10.1177/0272989X241263356
107. Inoue K, Adomi M, Efthimiou O, Komura T, Omae K, Onishi A, Tsutsumi Y, Fujii T, Kondo N, Furukawa TA. Machine learning approaches to evaluate heterogeneous treatment effects in randomized controlled trials: a scoping review. *J Clin Epidemiol*. 2024;176:111538. doi: 10.1016/j.jclinepi.2024.111538
108. Leist AK, Klee M, Kim JH, Rehkopf DH, Bordas SPA, Muniz-Terrera G, Wade S. Mapping of machine learning approaches for description, prediction, and causal inference in the social and health sciences. *Sci Adv*. 2022;8:eabk1942. doi: 10.1126/sciadv.abk1942
109. Wang M. Explainable machine-learning-based cardiovascular disease prediction in patients with hypertension: algorithm comparison and Shapley Additive exPlanations (SHAP) analysis. *Arch Cardiovasc Dis*. 2025. doi: 10.1016/j.acvd.2025.09.005
110. Li Z, Zhang B, Chao L, Tian X, Chen W, Liu C, Tian H. Identification of novel biomarkers for hypertension and ventricular remodeling based on transcriptomics and machine learning. *iScience*. 2025;28:113668. doi: 10.1016/j.isci.2025.113668
111. Bashir A, Rizwan MA, Bashir M. A machine learning-based model to estimate the risk of pulmonary hypertension in chronic kidney disease patients. *J Clin Hypertens (Greenwich)*. 2025;27:e70190. doi: 10.1111/jch.70190
112. Alam SF, Gonzalez Suarez ML. Transforming healthcare: the AI revolution in the comprehensive care of hypertension. *Clin Pract*. 2024;14:1357–1374. doi: 10.3390/clinpract14040109
113. Lopez-Martinez F, Nunez-Valdez ER, Crespo RG, Garcia-Diaz V. An artificial neural network approach for predicting hypertension using NHANES data. *Sci Rep*. 2020;10:10620. doi: 10.1038/s41598-020-67640-z

114. Carrasco-Ribelles LA, Llanes-Jurado J, Gallego-Moll C, Cabrera-Bean M, Monteagudo-Zaragoza M, Violan C, Zabaleta-Del-Olmo E. Prediction models using artificial intelligence and longitudinal data from electronic health records: a systematic methodological review. *J Am Med Inform Assoc*. 2023;30:2072–2082. doi: 10.1093/jamia/ocad168
115. Lee TC, Shah NU, Haack A, Baxter SL. Clinical implementation of predictive models embedded within electronic health record systems: a systematic review. *Informatics (MDPI)*. 2020;7:25. doi: 10.3390/informatics7030025
116. Ong JCL, Seng BJJ, Law JZF, Low LL, Kwa ALH, Giacomini KM, Ting DSW. Artificial intelligence, ChatGPT, and other large language models for social determinants of health: Current state and future directions. *Cell Rep Med*. 2024;5:101356. doi: 10.1016/j.xcrm.2023.101356
117. Das NC, Ghosh PK, Hossain MA, Shuvo UA, Talukder NR, Khatun F, Chowdhury MZI. Predicting hypertension and identifying most important factors among married women in Bangladesh using machine learning approach. *PLoS One*. 2025;20:e0335442. doi: 10.1371/journal.pone.0335442
118. Nouis SC, Uren V, Jariwala S. Evaluating accountability, transparency, and bias in AI-assisted healthcare decision- making: a qualitative study of healthcare professionals' perspectives in the UK. *BMC Med Ethics*. 2025;26:89. doi: 10.1186/s12910-025-01243-z
119. Saenz AD, Centi A, Ting D, You JG, Landman A, Mishuris RG; Mass General Brigham AI Governance Committee. Establishing responsible use of AI guidelines: a comprehensive case study for healthcare institutions. *NPJ Digit Med*. 2024;7:348. doi: 10.1038/s41746-024-01300-8
120. Panichella G, Garofalo M, Sasso L, Milazzo A, Fornaro A, Pioner JM, Bueno-Orovio A, van Gils M, Koivu A, Mainardi L, et al. Artificial intelligence applications in hypertrophic cardiomyopathy: turns and loopholes. *Eur Heart J Digit Health*. 2025;6:853–867. doi: 10.1093/ehjdh/ztaf086
121. Zhao Q, Zhang C, Zhang W, Zhang S, Liu Q, Guo Y. Applications and challenges of biomarker-based predictive models in proactive health management. *Front Public Health*. 2025;13:1633487. doi: 10.3389/fpubh.2025.1633487
122. Islam SMS, Talukder A, Awal MA, Siddiqui MMU, Ahamad MM, Ahammed B, Rawal LB, Alizadehsani R, Abawajy J, Laranjo L, et al. Machine learning approaches for predicting hypertension and its associated factors using population-level data from three south asian countries. *Front Cardiovasc Med*. 2022;9:839379. doi: 10.3389/fcvm.2022.839379
123. Hwang SH, Lee H, Lee JH, Lee M, Koyanagi A, Smith L, Rhee SY, Yon DK, Lee J. Machine learning-based prediction for incident hypertension based on regular health checkup data: derivation and validation in 2 independent nationwide cohorts in South Korea and Japan. *J Med Internet Res*. 2024;26:e52794. doi: 10.2196/52794
124. Kumar A, Goel S, Chaudhary A, Dutt S, Mishra VK, Kumar R. Artificial intelligence-based wearable sensing technologies for the management of cancer, diabetes, and COVID-19. *Biosensors*. 2025;15:756. doi: 10.3390/bios15110756
125. Chiang PH, Wong M, Dey S. Using wearables and machine learning to enable personalized lifestyle recommendations to improve blood pressure. *IEEE J Transl Eng Health Med*. 2021;9:2700513. doi: 10.1109/JTEHM.2021.3098173
126. Chen J, Wang Y. Personalized fitness recommendations using machine learning for optimized national health strategy. *Sci Rep*. 2025;15:41652. doi: 10.1038/s41598-025-25566-4
127. Passman JE, Hwang J, Tang J, Fagen M, Epps M, Peifer M, Howell JT, Cohen JB, Delgado MK, Wachtel H, et al. Active choice nudge to increase screening for primary aldosteronism in at-risk patients. *J Am Coll Surg*. 2025;240:46–59. doi: 10.1097/XCS.0000000000001221
128. Xu Y, Liu B, Huang X, Guo X, Suo N, Jiang S, Wang H. Artificial intelligence in primary aldosteronism: current achievements and future challenges. *Front Mol Biosci*. 2025;12:1660588. doi: 10.3389/fmolb.2025.1660588
129. Tamaru S, Suwanai H, Abe H, Sasaki J, Ishii K, Iwasaki H, Shikuma J, Ito R, Miwa T, Sasaki T, et al. Machine learning approach to predict subtypes of primary aldosteronism is helpful to estimate indication of adrenal vein sampling. *High Blood Press Cardiovasc Prev*. 2022;29:375–383. doi: 10.1007/s40292-022-00523-8
130. Makimoto H, Suzuki T. Machine learning-based screening for primary aldosteronism in hypertensive patients: overcoming underdiagnosis. *JACC Asia*. 2024;4:985–986. doi: 10.1016/j.jacasi.2024.10.015
131. Miao Y, Luo Y, Zhao Y, Wang H, Wu Y. Temporal trends and machine learning prediction for chronic kidney disease due to hypertension in young adults from 1990 to 2021: an analysis of the global burden of disease study 2021. *Ann Med*. 2025;57:2537916. doi: 10.1080/07853890.2025.2537916
132. Cheungpasitporn W, Athavale A, Ghazi L, Kashani KB, Colicchio T, Koyner JL, Chen J, Ix JH, Nadkarni G, Neyra JA. Transforming nephrology through artificial intelligence: a state-of-the-art roadmap for clinical integration. *Clin Kidney J*. 2026;19:sfag004. doi: 10.1093/ckj/sfag004
133. Maleki Varnosfaderani S, Forouzanfar M. The role of AI in hospitals and clinics: transforming healthcare in the 21st century. *Bioengineering (Basel)*. 2024;11:337. doi: 10.3390/bioengineering11040337
134. Gudigar A, Kadri NA, Raghavendra U, Samanth J, Maithri M, Inamdar MA, Prabhu MA, Hegde A, Salvi M, Yeong CH, et al. Automatic identification of hypertension and assessment of its secondary effects using artificial intelligence: a systematic review (2013-2023). *Comput Biol Med*. 2024;172:108207. doi: 10.1016/j.compbiomed.2024.108207
135. Estiko RI, Widyantoro B, Juzar DA, Yusup RM, Rakhmat IF, Rijanto E. Screening hypertension using non-laboratory risk factors with machine learning: a retrospective cross-sectional study in Indonesia. *BMJ Open*. 2025;15:e092364. doi: 10.1136/bmjopen-2024-092364
136. Skalidis I, Maurizi N, Salihu A, Fournier S, Cook S, Iglesias JF, Laforgia P, D'Angelo L, Garot P, Hovasse T, et al. Artificial intelligence and advanced digital health for hypertension: evolving tools for precision cardiovascular care. *Medicina (Kaunas)*. 2025;61:1597. doi: 10.3390/medicina61091597
137. O'Hagan E, McIntyre D, Laranjo L. The potential for a chat-based artificial intelligence model to facilitate educational messaging on hypertension. *Hypertension*. 2023;80:e128–e130. doi: 10.1161/HYPERTENSIONAHA.123.21395
138. Fang J, Lee VC, Ji H, Wang H. Enhancing digital health services: a machine learning approach to personalized exercise goal setting. *Digit Health*. 2024;10:20552076241233247. doi: 10.1177/20552076241233247
139. Xu H, Long H. The effect of smartphone app-based interventions for patients with hypertension: systematic review and meta-analysis. *JMIR Mhealth Uhealth*. 2020;8:e21759. doi: 10.2196/21759
140. Smith W, Colbert BM, Namouz T, Caven D, Ewing JA, Albano AW. Remote patient monitoring is associated with improved outcomes in hypertension: a large, retrospective, cohort analysis. *Healthcare*. 2024;12:1583. doi: 10.3390/healthcare12161583
141. Yao Q, Qiu B, He L, Wang Q, Zou J, Liang D, Wen S, Liu Y, Li G, Hu J, et al. Effects of artificial intelligence recognition-based telerehabilitation on exercise capacity in patients with hypertension: randomized controlled trial. *J Med Internet Res*. 2026;28:e81400. doi: 10.2196/81400
142. Ribeiro R, Martins R, Pereira H, Crista V, Souza J, Almeida R, Martinho D, Conceicao L, Freitas A, Marreiros G. A systematic review on wearable-enabled remote health monitoring. *Digit Health*. 2026;12:20552076261428387. doi: 10.1177/20552076261428387
143. Del-Valle-Soto C, Lopez-Pimentel JC, Vazquez-Castillo J, Nolazco-Flores JA, Velazquez R, Varela-Aldas J, Visconti P. A comprehensive review of behavior change techniques in wearables and IoT: implications for health and well-being. *Sensors (Basel)*. 2024;24:2429. doi: 10.3390/s24082429
144. Juyal A, Bisht S, Singh MF. Smart solutions in hypertension diagnosis and management: a deep dive into artificial intelligence and modern wearables for blood pressure monitoring. *Blood Press Monit*. 2024;29:260–271. doi: 10.1097/MBP.0000000000000711
145. Kim DY, Kim SH, Han SW, Ok JS, Son JW, Jeong JO, Kim EJ, Choi S, Jung IH, Ryu SK, et al. Evaluation of guideline adherence to hypertension-mediated organ damage screening in Korean patients with hypertension: results from the Korean Registry of Target Organ Damage in Hypertension (KorHR). *Clin Hypertens*. 2026;32:e11. doi: 10.5646/ch.2026.32.e11
146. Trimarco V, Izzo R, Mone P, Lembo M, Manzi MV, Pacella D, Falco A, Gallo P, Esposito G, Morisco C, et al. Therapeutic concordance improves blood pressure control in patients with resistant hypertension. *Pharmacol Res*. 2023;187:106557. doi: 10.1016/j.phrs.2022.106557
147. Trimarco V, Manzi MV, Izzo R, Mone P, Lembo M, Pacella D, Esposito G, Falco A, Morisco C, Gallo P, et al. The therapeutic concordance approach reduces adverse drug reactions in patients with resistant hypertension. *Front Cardiovasc Med*. 2023;10:1137706. doi: 10.3389/fcvm.2023.1137706
148. Shahab R, Rabbitt L, Molloy GJ. Clinician's attitudes & perspective on chemical adherence testing in hypertension (CATCH): a qualitative interview study. *Br J Clin Pharmacol*. 2026. doi: 10.1002/bcp.70462
149. Sheleme T, Bekele F, Olika W, Sefera B. Impact of medication therapy management intervention on medication adherence among adult patients comorbid with diabetes mellitus and hypertension at outpatient clinics in Southwest Ethiopia: a cluster randomized controlled trial. *Cardiovasc Diabetol Endocrinol Rep*. 2025;11:41. doi: 10.1186/s40842-025-00254-4
150. Hassam K, Funnell MP, Patel R, Gillies CL, Khunti K, Gupta P, Highton P. Interventions to improve medication adherence in people with hypertension: protocol for a systematic review and meta-analysis. *Health Sci Rep*. 2025;8:e71593. doi: 10.1002/hsr2.71593

151. Visco V, Izzo C, Mancusi C, Rispoli A, Tedeschi M, Virtuoso N, Giano A, Gioia R, Melfi A, Serio B, et al. Artificial intelligence in hypertension management: an ace up your sleeve. *JCDD*. 2023;10:74. doi: 10.3390/jcdd10020074
152. Griffin AC, Khairat S, Bailey SC, Chung AE. A chatbot for hypertension self-management support: user-centered design, development, and usability testing. *JAMIA Open*. 2023;6:ooad073. doi: 10.1093/jamiaopen/ooad073
153. Kurniawan MH, Handiyani H, Nuraini T, Hariyati RTS, Sutrisno S. A systematic review of artificial intelligence-powered (AI-powered) chatbot intervention for managing chronic illness. *Ann Med*. 2024;56:2302980. doi: 10.1080/07853890.2024.2302980
154. Yang M, Wu L, Zeng Y, Zhao C, Ye H, Wang J, Hao R. Smart community hypertension management: a narrative review of promises and challenges. *J Multidiscip Healthc*. 2026;19:583914. doi: 10.2147/JMDH.S583914
155. Griffin AC, Xing Z, Mikles SP, Bailey S, Khairat S, Arguello J, Wang Y, Chung AE. Information needs and perceptions of chatbots for hypertension medication self-management: a mixed methods study. *JAMIA Open*. 2021;4:ooab021. doi: 10.1093/jamiaopen/ooab021
156. Cutrona SL, McDannold SE, DeLaughter KL, Fix GM, Shimada SL, Bokhour BG, Gordon HS, Pope C, Smith BM, Ndiwane N, et al. Text messaging and video stories to support hypertension self-management in black veterans: a randomized clinical trial. *JAMA Netw Open*. 2025;8:e2541342. doi: 10.1001/jamanetworkopen.2025.41342
157. Maeda T, Sakamoto Y, Hosoki S, Satoh A, Koyoshi R, Yamashita S, Arima H. Does clinical practice supported by artificial intelligence improve hypertension care management? A pilot systematic review. *Hypertens Res*. 2024;47:2312–2316. doi: 10.1038/s41440-024-01771-y
158. Choudhry NK, Kronish IM, Vongpatanasin W, Ferdinand KC, Pavlik VN, Egan BM, Schoenthaler A, Houston Miller N, Hyman DJ; American Heart Association Council on Hypertension; Council on Cardiovascular and Stroke Nursing; and Council on Clinical Cardiology, Council on C, Stroke N, Council on Clinical C. Medication adherence and blood pressure control: a scientific statement from the American Heart Association. *Hypertension*. 2022;79:e1–e14. doi: 10.1161/HYP.0000000000000203
159. Layton AT. AI, machine learning, and ChatGPT in hypertension. *Hypertension*. 2024;81:709–716. doi: 10.1161/HYPERTENSIONAHA.124.19468
160. Kim SE, Lee CJ. Can Artificial Intelligence Change the Practice of Managing Hypertension? *Korean Circ J*. 2022;52:795–796. doi: 10.4070/kcj.2022.0254
161. Aryal S, Manandhar I, Mei X, Yeoh BS, Tummala R, Saha P, Osman I, Zubcevic J, Durgan DJ, Vijay-Kumar M, et al. Combating hypertension beyond genome-wide association studies: microbiome and artificial intelligence as opportunities for precision medicine. *Camb Prism Precis Med*. 2023;1:e26. doi: 10.1017/pcm.2023.13
162. Vaura F, Kauko A, Suvila K, Havulinna AS, Mars N, Salomaa V, Cheng S, Niiranen T; FinnGen. Polygenic risk scores predict hypertension onset and cardiovascular risk. *Hypertension*. 2021;77:1119–1127. doi: 10.1161/HYPERTENSIONAHA.120.16471
163. Varzideh F, Pande S, Jankauskas SS, Mone P, Kansakar U, Santulli G. Artificial intelligence in neurocardiology: decoding brain–heart network interactions for clinical and translational insights. *Front Neurosci*. 2026;20:1788653. doi: 10.3389/fnins.2026.1788653
164. Procopio A, Cesarelli G, Donisi L, Merola A, Amato F, Cosentino C. Combined mechanistic modeling and machine-learning approaches in systems biology - A systematic literature review. *Comput Methods Programs Biomed*. 2023;240:107681. doi: 10.1016/j.cmpb.2023.107681
165. Li K, Samiei S, Pikulska D, Foecking S, Kuppe C. Advancing cardiovascular research with single-cell and spatial transcriptomics. *Circ Res*. 2026;138:e325795. doi: 10.1161/CIRCRESAHA.125.325795
166. Hayes CN, Nakahara H, Ono A, Tsuge M, Oka S. From omics to multi-omics: a review of advantages and tradeoffs. *Genes (Basel)*. 2024;15:1551. doi: 10.3390/genes15121551
167. Liu FQ, Mo Y. Predicting hypertension using PPG sensor data and demographic factors: a machine learning approach. *Technol Health Care*. 2026;34:16–25. doi: 10.1177/09287329251375640
168. Zhong X, Zhao T, Lv S, Zhang G, Li J, Liu D, Jiao H. Development and interpretation of a machine learning predictive model for early cognitive impairment in hypertension associated with environmental factors. *Front Cardiovasc Med*. 2025;12:1477185. doi: 10.3389/fcvm.2025.1477185
169. Zhang Z, Ye J. Predicting mortality in critically ill patients with hypertension using machine learning and deep learning models. *Front Cardiovasc Med*. 2025;12:1568907. doi: 10.3389/fcvm.2025.1568907
170. He S, Zhong X, Chen G, Li L. U-shaped association between serum chloride and hypertension risk with nadir around 103 mmol/L: insights from regression and interpretable machine learning (XGBoost/SHAP) using NHANES 2017-2018. *Front Physiol*. 2025;16:1612895. doi: 10.3389/fphys.2025.1612895
171. Banji D, Banji OJF. Pharmacogenomic insights into angiotensin converting enzyme inhibitors and calcium channel blockers for personalized hypertension treatment. *J Hypertens*. 2026;44:250–262. doi: 10.1097/HJH.0000000000004212
172. Naderi N, Jolfayi AG, Azimi A, Maleki M, Kalayinia S. Pharmacogenomics in cardiac therapy: personalizing treatment for heart health. *Biomed Pharmacother*. 2025;190:118392. doi: 10.1016/j.biopha.2025.118392
173. Rysz J, Franczyk B, Rysz-Gorzynska M, Gluba-Brzozka A. Pharmacogenomics of hypertension treatment. *IJMS*. 2020;21:4709. doi: 10.3390/ijms21134709
174. Kayani M, Sangeetha GK, Sarangi S, Gaddamanugu LS, Sharma S, Adedara VO, Abdallah S, Katz K, Mora GR, Kommuru S, et al. Pharmacogenomics and its role in cardiovascular diseases: a narrative literature review. *CCR*. 2025;21::e1573403X1334668. doi: 10.2174/011573403x334668241227074314
175. Eadon MT, Kanuri SH, Chapman AB. Pharmacogenomic studies of hypertension: paving the way for personalized antihypertensive treatment. *Expert Rev Precis Med Drug Dev*. 2018;3:33–47. doi: 10.1080/23808993.2018.1420419
176. Shen Y, Zhang P, Luo J, Chen S, Gu S, Lin Z, Tang Z. Artificial intelligence drives advances in multi-omics analysis and precision medicine for sepsis. *Biomedicines*. 2026;14:261. doi: 10.3390/biomedicines14020261
177. Mani S, Lalani SR, Pammi M. Genomics and multiomics in the age of precision medicine. *Pediatr Res*. 2025;97:1399–1410. doi: 10.1038/s41390-025-04021-0
178. Wang S, Shi Y, Sui M, Shen J, Chen C, Zhang L, Zhang X, Ren D, Wang Y, Yang Q, et al. Telephone follow-up based on artificial intelligence technology among hypertension patients: Reliability study. *J Clin Hypertens (Greenwich)*. 2024;26:656–664. doi: 10.1111/jch.14823
179. Smith LA, Cahill JA, Lee JH, Graim K. Equitable machine learning counteracts ancestral bias in precision medicine. *Nat Commun*. 2025;16:2144. doi: 10.1038/s41467-025-57216-8
180. Gao Y, Sharma T, Cui Y. Addressing the challenge of biomedical data inequality: an artificial intelligence perspective. *Annu Rev Biomed Data Sci*. 2023;6:153–171. doi: 10.1146/annurev-biodatasci-020722-020704
181. Pham T. Ethical and legal considerations in healthcare AI: innovation and policy for safe and fair use. *R Soc Open Sci*. 2025;12:241873. doi: 10.1098/rsos.241873
182. Owen CM, Bacardit J, Tan MP, Saedon NI, Goh CH, Newton JL, Frith J. Artificial intelligence driven clustering of blood pressure profiles reveals frailty in orthostatic hypertension. *Exp Physiol*. 2025;110:230–247. doi: 10.1113/EP091876
183. Gala D, Behl H, Shah M, Makaryus AN. The role of artificial intelligence in improving patient outcomes and future of healthcare delivery in cardiology: a narrative review of the literature. *Healthcare (Basel)*. 2024;12:481. doi: 10.3390/healthcare12040481
184. Barrett M, Boyne J, Brandts J, Brunner-La Rocca HP, De Maesschalck L, De Wit K, Dixon L, Eurlings C, Fitzsimons D, Golubnitschaja O, et al. Artificial intelligence supported patient self-care in chronic heart failure: a paradigm shift from reactive to predictive, preventive and personalised care. *EPMA J*. 2019;10:445–464. doi: 10.1007/s13167-019-00188-9
185. Kassab J, El Dahdah J, Chedid El Helou M, Layoun H, Sarraju A, Laffin LJ, Cho L, Kapadia SR, Collier P, Harb SC. Assessing the accuracy of an online chat-based artificial intelligence model in providing recommendations on hypertension management in accordance with the 2017 American College of Cardiology/American Heart Association and 2018 European Society of Cardiology/European Society of Hypertension Guidelines. *Hypertension*. 2023;80:e125–e127. doi: 10.1161/HYPERTENSIONAHA.123.21183
186. Samal L, Kilgallon JL, Lipsitz S, Baer HJ, McCoy A, Gannon M, Noonan S, Dunk R, Chen SW, Chay WI, et al. Clinical decision support for hypertension management in chronic kidney disease: a randomized clinical trial. *JAMA Intern Med*. 2024;184:484–492. doi: 10.1001/jamainternmed.2023.8315
187. Yu Y, Gomez-Cabello CA, Haider SA, Genovese A, Prabha S, Trabilsy M, Collaco BG, Wood NG, Bagaria S, Tao C, et al. Enhancing clinician trust in AI diagnostics: a dynamic framework for confidence calibration and transparency. *Diagnostics*. 2025;15:2204. doi: 10.3390/diagnostics15172204
188. Harishbhai Tilala M, Kumar Chenchala P, Choppadandi A, Kaur J, Naguri S, Saoji R, Devaguptapu B. Ethical considerations in the use of artificial intelligence and machine learning in health care: a comprehensive review. *Cureus*. 2024;16:e62443. doi: 10.7759/cureus.62443

189. Radanliev P. Privacy, ethics, transparency, and accountability in AI systems for wearable devices. *Front Digit Health*. 2025;7:1431246. doi: 10.3389/fdgth.2025.1431246
190. Wu Y, Xin B, Wan Q, Ren Y, Jiang W. Risk factors and prediction models for cardiovascular complications of hypertension in older adults with machine learning: a cross-sectional study. *Heliyon*. 2024;10:e27941. doi: 10.1016/j.heliyon.2024.e27941
191. Subbaswamy A, Sahiner B, Petrick N, Pai V, Adams R, Diamond MC, Saria S. A data-driven framework for identifying patient subgroups on which an AI/machine learning model may underperform. *NPJ Digit Med*. 2024;7:334. doi: 10.1038/s41746-024-01275-6
192. Obra JK, Singh C, Watkins K, Feng J, Obermeyer Z, Kornblith A. Potential for algorithmic bias in clinical decision instrument development. *NPJ Digit Med*. 2025;8:762. doi: 10.1038/s41746-025-02119-7
193. Bitomsky L, Nissen M, Kowatsch T. Equity by design principles for digital health interventions. *Int J Equity Health*. 2025;24:271. doi: 10.1186/s12939-025-02645-6
194. Mennella C, Maniscalco U, De Pietro G, Esposito M. Ethical and regulatory challenges of AI technologies in healthcare: a narrative review. *Heliyon*. 2024;10:e26297. doi: 10.1016/j.heliyon.2024.e26297
195. Carvalho E, Mascarenhas M, Pinheiro F, Correia R, Balseiro S, Barbosa G, Guerra A, Oliveira D, Moura R, Martins Dos Santos A, et al. Predetermined change control plans: guiding principles for advancing safe, effective, and high-quality AI-ML technologies. *JMIR AI*. 2025;4:e76854. doi: 10.2196/76854
196. Abd-Alrazaq A, Solaiman B, Mekki YM, Al-Thani D, Farooq F, Alkubeyyer M, Abubacker MZ, AlSaad R, Aziz S, Serag A, et al. Hype vs reality in the integration of artificial intelligence in clinical workflows. *JMIR Form Res*. 2025;9:e70921. doi: 10.2196/70921
197. Kilfoy A, Hsu TC, Stockton-Powdrell C, Whelan P, Chu CH, Jibb L. An umbrella review on how digital health intervention co-design is conducted and described. *NPJ Digit Med*. 2024;7:374. doi: 10.1038/s41746-024-01385-1
198. Chen Z, Liang N, Zhang H, Li H, Yang Y, Zong X, Chen Y, Wang Y, Shi N. Harnessing the power of clinical decision support systems: challenges and opportunities. *Open Heart*. 2023;10:e002432. doi: 10.1136/openhrt-2023-002432
199. Babapour Mofrad F. Evolution of AI-based software as a medical device: from static tools to adaptive clinical partners. *Expert Rev Med Devices*. 2026;1–4. doi: 10.1080/17434440.2026.2638365
200. Mahmud A, Dwivedi G, Chow BJW. Exploring the integration of artificial intelligence in cardiovascular medical education: unveiling opportunities and advancements. *Can J Cardiol*. 2024;40:1946–1949. doi: 10.1016/j.cjca.2024.06.014