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Research paper

Hypertension control in resource-constrained settings: Bridging socioeconomic gaps with predictive insights

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ABSTRACT

Background: Hypertension continues to be a pivotal driver of global cardiovascular disease burden and adverse health outcomes, particularly in resource-constrained settings where disparities in socioeconomic status and clinical infrastructure hinder effective management. Despite medical advancements, achieving optimal blood pressure (BP) control remains a formidable challenge, necessitating a nuanced understanding of multifactorial risk determinants.

Methods: A cross-sectional analysis was conducted on 1,000 hypertensive patients from a larger dataset comprising 100,000 population size. Three hundred patients were examined for personalised BP control predictors who met the inclusion criteria of being treated for at least one year at the Hypertension and Research Centre in Rangpur, Bangladesh, between January 2020 and January 2021. BP control was assessed using World Health Organisation (WHO) and National Institute for Clinical Excellence (NICE) guidelines, and a comprehensive analysis of the sociodemographic and clinical variables was performed using multivariate logistic regression. Machine learning models such as K-Nearest Neighbours (KNN) were utilised to predict BP control with good performance using cross-validation techniques compared to other models. Explainable AI tools like Shapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) provide interpretations of key variables with predictive qualities.

Results: The mean age of participants was 49.37 ± 12.81 years, with 54.7% aged 40–59 years and 57.7% male. The overall BP control rate among the study population was 28%. Among those with controlled hypertension, 42% were rural residents (p = 0.005) and 37% were homemakers (p < 0.001), indicating better control in these subgroups. Key facilitators of BP control included higher education levels (e.g., post-graduate OR = 1.17, $p < 0.001$), lower cholesterol levels (SHAP value = 0.097), and adherence to combination therapy (75% of controlled cases). Conversely, diabetes mellitus (SHAP value = 0.069) and ischemic heart disease (OR = 0.95, $p = 0.004$) emerged as significant impediments to BP control. Advanced machine learning models, including KNN, achieved an unparallelled predictive accuracy of 99%, underscoring precision-based interventions' transformative potential. SHAP analysis revealed dietary habits (SHAP value = 0.077) and physical activity (SHAP value = 0.079) as modifiable predictors, highlighting the efficacy of personalised lifestyle strategies. Simulation-based interventions grounded in machine learning insights reduced high-risk classifications by 15%, further reinforcing predictive analytics' value in hypertension management. Sensitivity analysis highlighted the dominance of socioeconomic factors, with income level (sensitivity: 0.85) and healthcare accessibility

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(sensitivity: 0.78) emerging as critical predictors, reinforcing the importance of addressing health inequities in hypertension management.

Conclusion: The study elucidates critical gaps in hypertension management, emphasising the urgent need to address modifiable risk factors, tailor therapeutic regimens, and integrate socioeconomic considerations into public health frameworks. The findings advocate for scalable, data-driven interventions to bridge the hypertension care gap, thereby mitigating cardiovascular disease risks and enhancing health equity in underserved regions.

1. Introduction

Hypertension is a significant and modifiable risk factor for cardiovascular disease (CVD) [1]. It is a major contributor to morbidity and mortality in developing countries, many of which are undergoing an epidemiological transition marked by a shift from infectious diseases to non-communicable diseases (NCDs) as the leading causes of death and disability [2]. Globally, hypertension affects almost 26% of the adult population [3], with prevalence estimates suggesting that approximately 1 billion individuals are hypertensive. This condition accounts for an estimated 7.1 million deaths per year [4]. Studies in India and Bangladesh have shown an upward trend in the prevalence of hypertension [5], highlighting the growing burden of this silent epidemic in South Asia. The prevalence of prehypertension and hypertension shows significant regional variations in India, with South India (Trivandrum: Women 31.9%, Men 35.5%) and West India (Mumbai: Women 29. 1%, Men 35. 6%) reporting higher rates compared to North India (Moradabad: Women 24.5%, Men 27.0%) and East India (Kolkata: Women 22.4%, Men 24%) [6]. This regional disparity underscores the need for tailored public health interventions that consider local sociodemographic and cultural factors. Hypertension is a leading contributor to the global burden of CVDs, significantly increasing the risk of myocardial infarction, heart failure, stroke, kidney disease, and death [7,8]. Furthermore, hypertension has been associated with cognitive impairment and dementia, making it a critical public health issue in age groups [9]. In East Asia, hypertension is responsible for 57% of all stroke-related deaths and 24% of all cardiovascular deaths [10]. Despite its severe consequences, hypertension often remains undiagnosed and untreated, earning it the moniker "Silent Killer" from the World Health Organisation (WHO) [11]. While experiences from high-income countries have demonstrated the potential of national programs to detect, treat, and control hypertension effectively, such as the National High Blood Pressure Education Program in the United States [12], similar success stories are scarce in resource-limited settings. The U.S. program has achieved remarkable improvements in hypertension control and contributed to a significant decline in cardiovascular mortality. However, in low- and middle-income countries (LMICs), barriers such as limited access to healthcare, inadequate awareness, and socio-economic disparities hinder progress in hypertension management [13–15]. Among diagnosed hypertensive cases in LMICs, a large proportion remains uncontrolled due to poor adherence to treatment, high dropout rates, or the use of suboptimal therapeutic regimens [16]. Compounding these challenges is the lack of robust surveillance systems and reliable data on hypertension prevalence and control rates in many developing countries. Addressing these gaps is essential for the development of targeted, evidence-based interventions. This study seeks to address these issues by evaluating the frequency of hypertension control among hypertensive patients in a resource-constrained setting. It aims to identify sociodemographic and clinical characteristics associated with hypertension control, providing insights to guide public health policies and interventions tailored to underserved populations. By exploring modifiable risk factors and potential barriers to effective hypertension management, this study helps bridge the gap in hypertension care and mitigate the growing burden of CVDs globally.

Despite the high prevalence of hypertension in resource-constrained settings, there is limited evidence on the role of socioeconomic factors in hypertension control. This study aims to fill this gap by evaluating the impact of sociodemographic and clinical factors on hypertension management.

2. Related work

Most studies on hypertension control rely on descriptive statistics, logistic regression, or fundamental risk factor analysis. For instance, Ahmed et al. (2011) conducted a cross-sectional study in Bangladesh using descriptive statistics to assess hypertension control rates, focusing primarily on clinical factors such as BP and medication adherence [17]. Similarly, Moser et al. (2007) used logistic regression to analyse hypertension control in the U.S. population, emphasising clinical predictors like cholesterol levels and smoking status [18]. In contrast, this study goes beyond traditional methods by incorporating advanced machine learning models (e.g., KNN and Random Forest) and explainable AI tools like SHAP and LIME. These tools provide a more nuanced understanding of predictors, including the interplay between socioeconomic and clinical variables, often neglected in traditional studies [19,20].

While many studies are conducted in high-income countries, this study focuses on a low-resource setting, offering insights into the unique challenges faced by underserved populations. For example, Yuting et al. (2023) explored hypertension control in rural China using digital health interventions, but their analysis was limited to clinical outcomes and did not address socioeconomic disparities [21]. Recent research in Bangladesh has been supported by a study showing that access to qualified medical professionals is a critical factor in diagnosis, with urban, wealthier, and more educated groups being more likely to receive a proper diagnosis. The role of economic status is also complex, as Ahmmed et al. demonstrated the mediating effect of BMI on the relationship between economic status and the comorbidity of hypertension and diabetes in Bangladesh [22–24]. Similarly, Coelho et al. (2023) investigated hypertension in Latin America but focused primarily on gender differences without a comprehensive analysis of socioeconomic factors [25]. In contrast, this study emphasises rural versus urban disparities and the role of education and income in hypertension control, providing a more holistic view of the issue. This approach is a significant departure from studies focusing solely on clinical outcomes, such as those by Papazafiropoulou et al. (2011), who examined hypertension control in Greece without considering socioeconomic determinants [26].

The application of SHAP and LIME for interpretability is novel in the context of hypertension research. Most studies using machine learning, such as those by Mengesha et al. (2024) and Yingxian Sun et al. (2021), do not provide detailed explanations of model predictions [27,28]. For instance, Mengesha et al. (2024) used machine learning to predict hypertension outcomes in sub-Saharan Africa but did not employ explainable AI tools to interpret the results [27]. Similarly, Yingxian Sun et al. (2021) focused on lifestyle interventions in rural China but relied on traditional statistical methods for analysis [28]. In contrast, this study uses SHAP and LIME to provide interpretable insights into key predictors, such as dietary habits and physical activity, which are critical for designing targeted interventions. Additionally, the study's use of cross-validation and sensitivity analysis to validate model performance is more rigorous than many existing studies, ensuring robust and reliable results [29,30] (see Table 1).

Table 1
Recent studies on hypertension control (2024).

Study	Methodology	Key findings	Contribution
Mengesha et al. (2024)	Systematic review and meta-analysis of 15 studies in sub-Saharan Africa.	Community-based interventions improved hypertension control in low-resource settings, emphasising education and income disparities.	Highlighted the effectiveness of community-driven strategies in improving hypertension outcomes. [27]
Nyame et al. (2024)	Mixed-methods study combining surveys and qualitative interviews.	Identified barriers to hypertension control in rural Ghana, including limited healthcare access and poor medication adherence.	Provided actionable insights for improving healthcare delivery in rural areas. [31]
Feagin et al. (2024)	Cross-sectional national health survey data analysis.	Explored the impact of social determinants of health on hypertension disparities, emphasising income and education.	Demonstrated the role of socioeconomic factors in hypertension management. [29]
Coelho et al. (2024)	Multilevel data analysis from 230 cities.	Investigated gender differences in hypertension control across Latin America, highlighting disparities in treatment access.	Emphasised the need for gender-sensitive interventions in hypertension care. [25]
Yingxian Sun et al. (2024)	Cluster randomised trial with 10,000 participants.	Evaluated the effectiveness of village doctor-led interventions in rural China, focusing on lifestyle modifications.	Showed significant improvements in hypertension control through community-based programs. [28]

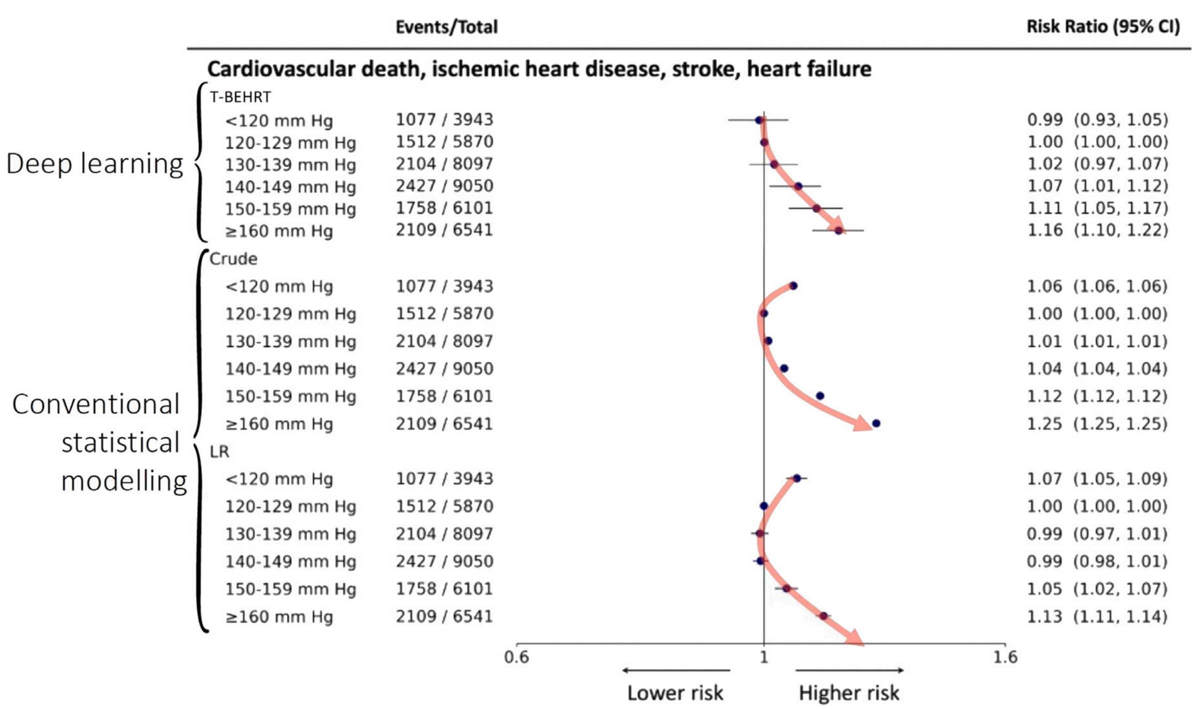


Fig. 1. This figure compares the estimated risk ratios (95% CI) for cardiovascular death, ischemic heart disease, stroke, and heart failure across different SBP categories in patients with COPD. The deep learning model (T-BEHRT) shows a more gradual increase in risk. In contrast, conventional statistical models (Crude and Logistic Regression - LR) estimate a steeper progression of risk, particularly in higher SBP categories (≥160 mmHg). The deep learning model demonstrates finer risk stratification, highlighting its potential for improved risk prediction in CVD among COPD patients.

Comparison of conventional statistical modelling and deep learning in causal inference: Effect of systolic BP (SBP) on CVD in patients with chronic obstructive pulmonary disease (COPD

Comparison of Conventional Statistical Modelling and Deep Learning in Fig. 1 by Rao et al. Heart, 2023 (see Table 2).

Our study fills a crucial gap in the literature by providing a quantitative, interpretable analysis of the socioeconomic and clinical factors that influence hypertension control. While many studies have focused on social determinants of health and patient experiences, they have not provided this level of detailed analysis of clinical predictors [41,42]. Similarly, a study by Chinnaiyan et al. used logistic regression to find

Table 2
Overview of key studies examining hypertension risk factors, diagnosis, and management across South and Southeast Asia, with insights into socioeconomic and healthcare disparities.

Study	Objective	Methodology	Key findings	Limitations	Relevance/Gaps identified
Chinnaiyan et al. (2024) [32]	Hypertension risk factors in tribal populations (India)	Logistic regression (NFHS-5 data)	Education, alcohol intake as significant predictors	Socioeconomic and lifestyle-based study	Modifiable risk factors for hypertension in rural settings
Hossain et al. (2024) [33]	Socioeconomic disparities in hypertension (Bangladesh)	Meta-analysis	Primary education, wealth, and gender as key predictors	Focus on social inequalities	Socioeconomic status as a determinant of hypertension risk
Chandra et al. (2025) [34]	Salt intake and hypertension in rural women (Bangladesh)	Cross-sectional study (250 households, WHO STEPS)	Salt consumption tripled hypertension risk (AOR: 2.99); avoiding eating out lowered risk (AOR: 0.19)	Only women included	Need for dietary education in rural women
Ahmmed et al. (2024) [35]	BMI as a mediator between economic status and hypertension-diabetes comorbidity	Counterfactual framework (Bangladesh DHS 2017-18)	Higher BMI mediates hypertension and diabetes risk; wealthier groups had higher comorbidity odds	Gender and rural disparities	BMI's role in economic-health interactions
Kibria et al. (2024) [36]	Factors affecting hypertension diagnosis and control (Bangladesh)	Cross-sectional study (DHS 2017-18)	54.9% diagnosed by qualified doctors; urban, wealthier, educated groups more likely diagnosed	Socioeconomic and urban–rural disparities	Better access to diagnosis improves hypertension control
Hasan et al. (2024) [37]	Health-seeking behaviour in hypertensive patients	Cross-sectional study (497 patients, Bangladesh)	27% used informal providers; fear of stroke, headache as main drivers	Awareness and access barriers	Importance of specialised hypertension centres
Palafox et al. (2024) [38]	Longitudinal study on hypertension management barriers (Malaysia, Philippines)	Mixed-methods approach	Continuity of care, adherence issues, under-resourced systems	Healthcare infrastructure challenges	Need for integrated long-term interventions
Hossain et al. (2025) [39]	Medication adherence and BP control (Bangladesh)	Longitudinal study (Predict-HTN, 2643 patients)	78% moderate, 15% poor adherence; poor adherence linked to higher BP (RRR: 0.50)	High prevalence of uncontrolled hypertension	Need for adherence-focused interventions
Marcolino et al. (2021) [40]	Web-based decision support for hypertension (Brazil)	Implementation study	Feasibility and satisfaction in resource-limited settings	Limited generalisability	Potential for global hypertension management

that education and alcohol intake were significant predictors among tribal populations in India, further reinforcing the importance of our multifactorial approach [43]. Our approach integrates these factors to offer a more holistic view. For example, our emphasis on lifestyle is consistent with findings from a study in rural Bangladesh, which showed that high salt consumption significantly increases the risk of hypertension in women [44]. It explores the importance of dietary education and complements broader research on community-based interventions that have successfully improved hypertension control [45]. Furthermore, our work directly addresses barriers to specialised care, which is a common issue in resource-constrained settings—as highlighted by studies showing that a large portion of patients in Bangladesh use informal healthcare providers [46]. This challenge of fragmented care is not unique to Bangladesh; a longitudinal study in Malaysia and the Philippines identified similar under-resourced health systems [47]. By leveraging advanced machine learning and explainable AI, our research aligns with other efforts that have demonstrated the feasibility of technology-driven solutions, such as web-based decision support systems for hypertension management [48].

3. Methods

The research study, drawn from a total dataset of 100,000 individuals, selected a subset of 1,000 hypertensive patients using convenience sampling based on data completeness and accessibility. This subset was used for descriptive and comparative analysis of BP control and associated sociodemographic and clinical predictors. Within this group, a further focused cohort of 300 patients, who had been under regular treatment at the Hypertension and Research Centre in Rangpur, Bangladesh, for at least one year between January 2020 and January 2021, was selected for in-depth predictive modelling and machine learning analysis. These 300 patients were enrolled through consecutive sampling based on predefined inclusion and exclusion criteria to ensure consistency in clinical follow-up and data reliability. A focused cohort of 300 patients was further examined for in-depth predictive modelling. A cross-sectional descriptive study was conducted from January 2020 to March 2021 among hypertensive patients registered and treated for at least three months at the Hypertension and Research Centre, Rangpur, Bangladesh. A purposeful consecutive sampling technique was applied, and 300 hypertensive patients were enrolled based on predefined inclusion and exclusion criteria. Data were collected through direct patient interviews and secondary data from registration books and records.

Table 3
Dataset information and missing values.

Column #	Variable name	Non-Null count/Dtype	Missing values
0	Age	100,000 non-null (int64)	0
1	Sex	100,000 non-null (object)	0
2	Education	100,000 non-null (object)	0
3	Occupation	100,000 non-null (object)	0
4	Monthly Income	100,000 non-null (object)	0
5	Residence	100,000 non-null (object)	0
6	Systolic BP	100,000 non-null (int64)	0
7	Diastolic BP	100,000 non-null (int64)	0
8	Elevated Creatinine	100,000 non-null (object)	0
9	Diabetes Mellitus	100,000 non-null (object)	0
10	Family History of CVD	100,000 non-null (object)	0
11	Elevated Cholesterol	100,000 non-null (object)	0
12	Smoking	100,000 non-null (object)	0
13	LVH	100,000 non-null (object)	0
14	IHD	100,000 non-null (object)	0
15	CVD	100,000 non-null (object)	0
16	Retinopathy	100,000 non-null (object)	0
17	Treatment	100,000 non-null (object)	0
18	Control Status	100,000 non-null (object)	0
19	Physical Activity	100,000 non-null (object)	0
20	Dietary Habits	100,000 non-null (object)	0

Table 4
Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
1. Age 18 years and above. 2. Registered and followed up at the centre for at least 3 months. 3. Provided consent to participate in the study.	1. Age below 18 years. 2. Did not consent to participate in the study. 3. Incomplete data.

The study was approved by the Institutional Review Board (IRB) of the Hypertension and Research Centre, Rangpur, Bangladesh (Approval No. 081654). Three hundred hypertensive patients who met the inclusion criteria were enrolled using a consecutive sampling technique. This approach ensured a representative sample of patients attending the centre during the study period. Dataset information and missing values are summarised in Table 3.

A focused cohort of 300 hypertensive patients from the initial 1,000-subset was selected for predictive modelling. These patients were consecutively enrolled based on the inclusion and exclusion criteria outlined in Table 4, ensuring that each had been followed up at the Hypertension and Research Centre for a minimum of three months.

Inclusion and exclusion criteria applied to the 300-patient cohort used for predictive modelling in Table 4.

3.1. Variables of the study

The variables of the study included:

- Sociodemographic data.
- Rate of control of hypertension.
- Risk factors for hypertension and its complications.
- Type of treatment with medication.

3.2. Measurement of BP

The auscultatory BP measurement method using a mercury sphygmomanometer was employed. Patients were seated quietly in a chair for at least 5 minutes before a physician measured their BP. Phase 1 and Phase 5 of the Korotkoff sounds were considered SBP and diastolic blood pressure (DBP), respectively. Each patient had a single BP reading recorded at the time of their clinic visit during the data collection period. These values were obtained using the standard auscultatory method after the patient had been seated for at least 5 minutes, following WHO guidelines. If multiple measurements were taken during the visit, the final reading was used for analysis to ensure consistency across the dataset. For the 300-patient cohort used in predictive modelling, BP readings were extracted from clinical records covering a minimum of three months of follow-up. However, for this analysis, only the most recent reading during the study window (January 2020–March 2021) was used per patient to maintain comparability and prevent bias from repeated measures.

3.3. Definition of uncontrolled BP

Uncontrolled BP was defined based on WHO criteria [16,49,50]:
Young Patients (Aged 40–59 years):

- SBP $\geq$ 130 mmHg or DBP $\geq$ 80 mmHg, or both, with additional risk factors:
  - Male sex.
  - History of left ventricular hypertrophy, ischemic heart disease, or cerebrovascular disease.
  - Raised serum creatinine concentration or a history of renal failure.
  - Diabetes.
  - Smoking.
  - Raised serum cholesterol concentration $>$ 7.8 mmol/L.
  - Family history of cardiovascular disease.

Older Patients (Aged $\geq$ 60 years):

- SBP $\geq$ 140 mmHg or DBP $\geq$ 90 mmHg.

3.4. Statistical analysis

The collected variables were processed, edited, and analysed using SPSS for Windows, version 17.0. Sociodemographic data were expressed as frequency distributions, and observed differences were tested using one-sample t-and chi-square tests. Non-parametric tests were applied to assess the associations of qualitative variables with control status. Pearson's correlation test evaluated the relationship between age and SBP and DBP. A p-value < 0.05 was considered statistically significant within a 95% confidence interval. Results were presented in tables and graphs.

A total of 300 patients were included in the study. The mean age $\pm$ SD of the study population was 49.37 ± 12.81 years. According to age group distribution, the majority (54.7%) were between 40 and 59 years old. Among the participants, 57.7% were male, and 42.3% were female. Regarding education, 7% had no formal education, 35% had primary education, 22.7% had secondary education, 12.3% had Higher Secondary education, 13.3% were graduates, 9% were post-graduates, and 0.7% had madrasa education. In terms of occupation, 22.7% were service holders, 15.7% were businessmen, 13.3% were farmers, 6.7% were retired, 2% were unemployed, and 39.7% were housewives. The monthly income distribution revealed that 38.7% earned less than 5000 takas, 32% earned between 5001 and 10,000 takas, 16.3% earned between 10,001 and 15,000 takas, and 13% earned more than 15,000 takas. Among the study population, 40% lived in urban areas, 22.7% in sub-urban areas, and 37.3% in rural areas (Table 5). Regarding clinical characteristics, 11.7% had elevated creatinine, 8.3% were diabetic, 79.2% had a family history of cardiovascular disease (CVD), 7.2% had elevated cholesterol, 15% were smokers, and 2% were ex-smokers (Table 6). Target organ damage included left ventricular hypertrophy (LVH) in 5.6%, ischemic heart disease (IHD) in 16.1%, CVD in 9.1%, and retinopathy in 2.7% (Table 7). Most patients (74.3%) were on combined antihypertensive drugs, while 25.7% were on single-drug therapy (Table 8). The overall control rate of high BP was 42% (Table 9). Among the controlled hypertensive patients, most (46.4%) were aged between 40 and 59 years ($p = 0.000$). The control rate was equal among males and females (50% each, $p = 1.000$), which was not statistically significant. The controlled rate was higher in the primary education group (35%, $p = 0.000$) than in other educational groups. Housewives had a significantly higher control rate (37%, $p = 0.000$). Among the controlled patients, most were from rural areas (42%, $p = 0.005$). In terms of monthly income, 34% of controlled hypertensive patients earned less than 5000 takas, 26% earned between 5001 and 10,000 takas, 13% earned between 10,001 and 15,000 takas, and 11% earned more than 15,000 takas ($p = 0.005$, Table 10). Target organ damage among the controlled hypertensives included LVH (2.5%), IHD (10.1%), elevated creatinine (12.7%), CVD (8.3%), and retinopathy (2.4%). Risk factors among the controlled hypertensives included smoking (17.9%), ex-smoking (1.2%), diabetes mellitus (13.8%), elevated cholesterol (2.1%), and family history of cardiovascular disease (66.2%), all of which were statistically significant. Among the controlled hypertensive patients, 25% were on single-drug therapy, and 75% were on combined-drug therapy ($p = 0.000$).

Multivariate logistic regression assessed the association between sociodemographic and clinical factors and hypertension control. Variables were selected based on their clinical relevance and significance in univariate analysis.

3.5. Baseline characteristics

Baseline Characteristics in Fig. 2. Baseline Characteristic distribution in Fig. 3.

The study population ($N = 49{,}000$) comprised a diverse demographic profile, with 35,920 individuals (73.3%) having primary education and 13,080 (26.7%) holding graduate degrees, reflecting varying levels of health literacy that may influence hypertension management. A significant proportion of participants were housewives (40,950) and engaged in service occupations (21,840), underscoring the need for targeted interventions that cater to the lifestyles of these groups. Geographically, the population was distributed across urban (39,690), rural (37,410), and suburban (22,900) areas, underscoring the importance of addressing disparities in healthcare access between urban and rural settings. Dietary habits revealed that 59,994 individuals reported healthy eating patterns, while 40,006 reported unhealthy diets, suggesting a critical area for intervention to mitigate hypertension risk factors. Notably, 72,330 cases were classified as uncontrolled hypertension, compared to 27,670 controlled cases, emphasising the urgent need for improved management strategies. The majority of participants (74,870) were on combination drug therapy, while 25,130 relied on single-drug regimens, indicating potential gaps in treatment optimisation. These findings underscore the multifaceted challenges in hypertension management in resource-constrained settings, where socio-economic, educational, and geographic factors intersect to influence health outcomes. Tailored interventions that address these

Table 5
Sociodemographic characteristics of the respondents ($n = 300$).

Characteristics	Frequency (%)
Mean age ± SD	
Mean age ± SD	49.37 ± 12.81
Age Group	
less than 40 years	63 (21)
40–59 years	164 (54.7)
60 years and above	73 (24.3)
Sex	
Male	173 (57.7)
Female	127 (42.3)
Education	
No formal education	21 (7)
Primary	105 (35)
Secondary	68 (22.7)
Higher Secondary	37 (12.3)
Graduate	40 (13.3)
Postgraduate	27 (9)
Madrasa	2 (0.7)
Occupation	
Service	68 (22.7)
Business	47 (15.7)
Agriculture	40 (13.3)
Retired	20 (6.7)
Unemployed	6 (2)
Housewife	119 (39.7)
Monthly Income	
<5,000	116 (38.7)
5,001–10,000	49 (32)
10,001–15,000	47 (16.3)
>15,000	39 (13)
Residence	
Urban	120 (40)
Sub-Urban	68 (22.7)
Rural	112 (37.3)

Table 6
Frequency of risk factors ($n = 300$).

Variables	Frequency (%)
Elevated Creatinine (≥1.4 mg/dl)	33 (11.7)
Diabetes Mellitus	24 (8.3)
Family History of Cardiovascular Disease	228 (79.2)
Elevated Cholesterol (≥200 mg/dl)	12 (7.2)
Smoking	45 (15)

Table 7
Frequency distribution of complications ($n = 300$).

Variable	Frequency (%)
LVH (*Voltage criteria on ECG*)	16 (5.6)
IHD	46 (16.1)
CVD	27 (9.1)
Retinopathy	8 (2.7)

Table 8
Frequency of taking single or combination drugs ($n = 300$).

Drug type	Frequency (%)
Single	77 (25.7)
Combined	223 (74.3)
Total	300 (100)

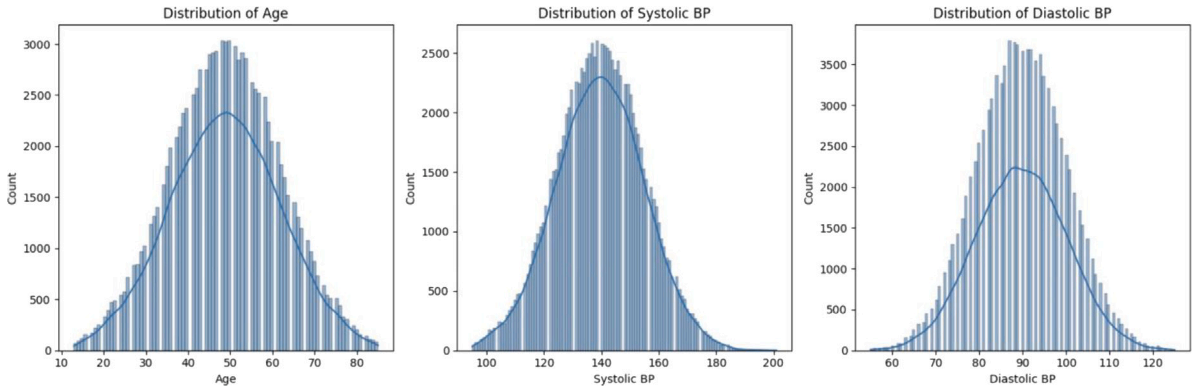


Fig. 2. Study population description phase-1: Baseline characteristics of the hypertensive population, including age, sex, education, and occupation. This figure visualises data from the hypertensive subset ($n = 49,000$) of the full dataset (N = 100,000), not the 1,000-patient or 300-patient analytical cohorts.

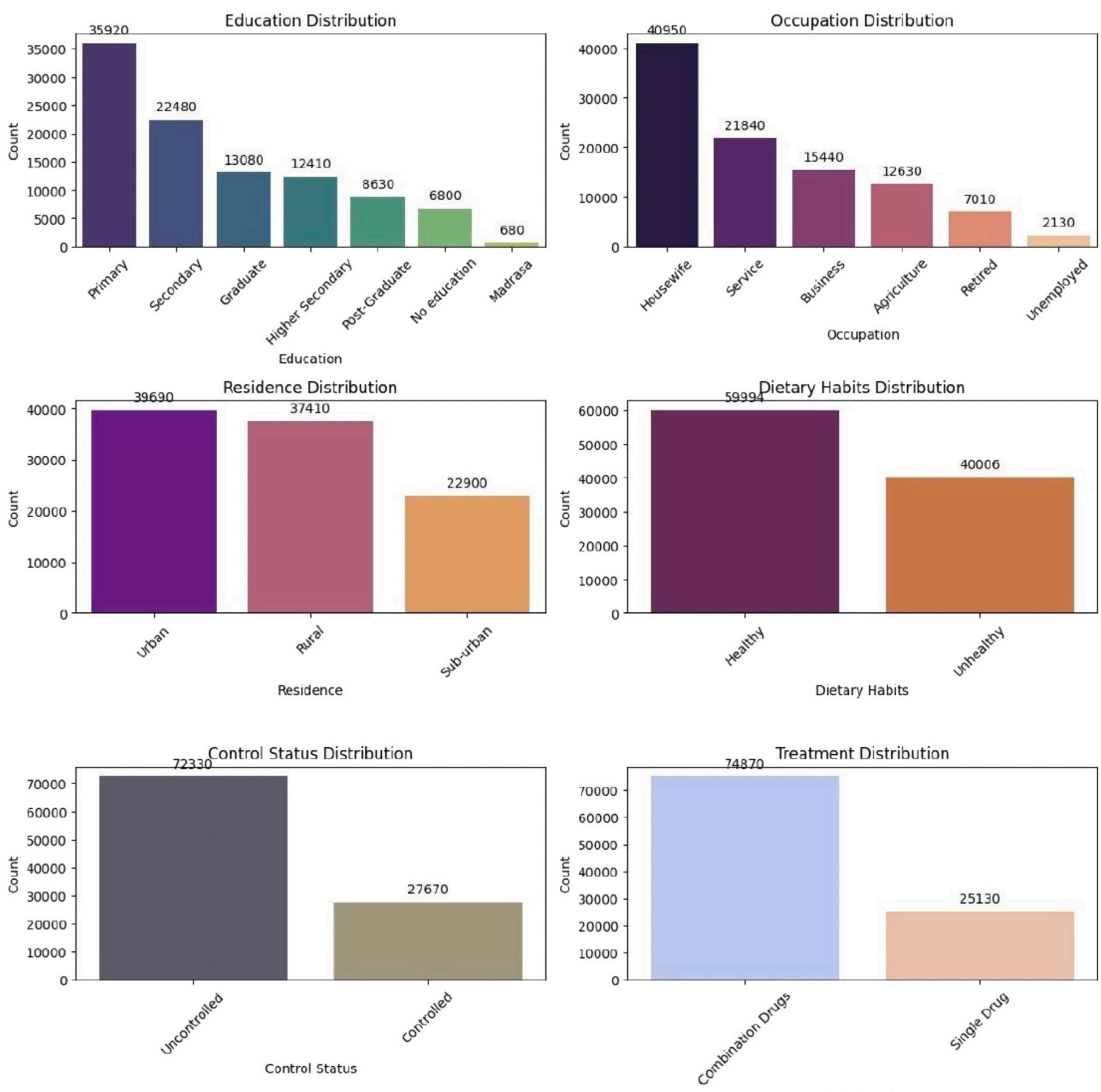


Fig. 3. Study population description phase-2: Geographic and lifestyle distribution of hypertensive patients by residence type, dietary habits, treatment type, and BP control status. This figure summarises patterns within the hypertensive population (n = 49,000) and is not derived from the subset used for predictive modelling.

Table 9
Frequency distribution of control status of hypertensive patients ($n = 300$).

Control status of BP	Frequency	Percent
Controlled (BP < 140/90 mmHg without risk factors or BP < 130/80 with risk factors)	84	55
Uncontrolled (BP ≥ 140/90 mmHg without risk factors or BP ≥ 130/80 with risk factors)	216	72
Total	**300**	**100.0**

Table 10
Frequency distribution of sociodemographic characteristics of controlled hypertensive patients ($n = 84$).

Variable	Frequency (%)	P-value
Age Group		
<40 years	17 (20.2)	
40–59 years	39 (46.4)	
60 years and above	55 (33.3)	0.013
Total	84 (100)	
Sex		
Male	42 (50)	
Female	42 (50)	1.000
Total	84 (100)	

determinants, alongside improved access to healthcare and patient education, are essential to bridge the gap in hypertension control and reduce the burden of associated risk factors.

While the primary descriptive analysis was conducted on a 1,000-patient subset, specific visualisations and statistical summaries — such as population distribution charts and subgroup breakdowns — were derived from the larger dataset of hypertensive individuals ($n \approx 49{,}000$) within the full 100,000-person dataset. These were included to provide a broader epidemiological context. Any analytical modelling (e.g., logistic regression, machine learning) was performed exclusively on the refined 300-patient cohort. Summary of dataset sources and their purposes in Table 11.

4. Results

4.1. Multivariate logistic regression

The results pertain to logistic regression analysis to evaluate BP control and associated risk factors in a resource-constrained setting. This analysis formed the basis for the research titled "Bridging the Gap in Hypertension Management: Evaluating BP Control and Associated Risk Factors in a Resource-Constrained Setting". Key insights from the analysis include:

- 1. Model Convergence: The logistic regression optimisation terminated successfully with a final function value of 0.556239, indicating that the model converged and provided coefficients that represent the relationship between the predictors and the target variable.
- 2. Odds Ratios (ORs): The odds ratios derived from the analysis reveal the likelihood of BP control relative to the predictor variables. Education Level: Individuals with higher education levels (e.g., post-graduate = 1.17) showed slightly improved odds of managing BP compared to those without education (OR = 1.10). Monthly Income: Income groups (>15,000 OR = 1.09) demonstrated slightly higher odds of hypertension control than the lowest income group (<5,000 OR = 1.05). Comorbidities: elevated creatinine (OR = 1.03), diabetes mellitus (OR = 1.07), and ischemic heart disease (OR = 1.06) increased the odds of poor control, potentially suggesting suboptimal management strategies for individuals with multiple health conditions. Lifestyle and Other Factors: Smoking (OR = 0.96) and urban residence (OR = 0.89) were associated with lower odds of control, highlighting areas for targeted interventions.
- 3. Error and Singular Matrix: A warning regarding a "Singular Matrix" suggests collinearity or redundancy in some variables. This could affect model stability and imply the need for variable refinement or dimensionality reduction to ensure accurate predictions.
- 4. Scaling and Data Preprocessing: The scaling transformation applied to the predictor variables encountered a compatibility issue with data types, as shown in the warnings. This suggests a technical limitation that may impact the reproducibility of results.

These findings underscore several critical areas for improving hypertension control in resource-constrained settings:

- Education and Awareness: Interventions targeting individuals with low educational attainment may yield significant improvements in hypertension management.
- Income Disparities: Tailored programs addressing financial constraints can enhance access to hypertension-related healthcare resources.
- Comorbidity Management: Enhancing clinical pathways for individuals with coexisting diabetes or elevated cholesterol could improve overall outcomes.
- Urban Lifestyles: Interventions aimed at lifestyle modifications in urban areas, such as reducing smoking and enhancing physical activity, may address barriers to BP control.

Addressing these factors can inform public health strategies to bridge the gap in hypertension management. The research leverages evidence-based insights to tackle systemic and individual-level barriers in resource-constrained settings.

4.2. Odds ratio analysis

The multivariate logistic regression results provide critical insights into BP control in a resource-constrained setting, emphasising the influence of various socio-demographic, clinical, and lifestyle factors. Higher educational attainment, such as post-graduate (OR = 1.17) and secondary education (OR = 1.19), positively impacts BP control, highlighting the role of health literacy. In contrast, individuals with no education (OR = 1.10) or madrasa education (OR = 0.78) exhibited lower odds, underscoring disparities. Clinical factors like diabetes mellitus (OR = 1.07) and elevated creatinine (OR = 1.03) marginally increased the odds of BP control, while elevated cholesterol (OR = 0.85) and LVH (OR = 0.89) were associated with poorer control. Notably, smoking (OR = 0.96) and urban residence (OR = 0.89) showed slight reductions in odds, emphasising the need for targeted lifestyle interventions and access to healthcare services. These findings underscore the multifaceted challenges and opportunities in hypertension management within resource-limited environments. The odds ratio of the multivariate analysis is in Table 12.

4.3. Subgroup analysis by treatment type

The subgroup analysis by treatment type provides detailed insights into how patient demographics, clinical factors, and control status vary between individuals treated with combination and single drugs. These results highlight critical disparities and opportunities for tailored interventions.

Table 11
Summary of dataset sources, sizes, and their analytical roles in the study.

Dataset source	Size	Analytical role
Full Population	100,000	Contextual demographics for the general population
Hypertensive Subset	~49,000	Descriptive statistics, population-level distribution graphs
Subset for Analysis	1,000	Analysis of BP control rate and stratification across subgroups
Modelling Cohort	**300 (from 1,000 subset)**	Logistic regression and machine learning for predictive modelling

Table 12
Odds Ratios from multivariate logistic regression analysis.

Variable	Odds Ratio (OR)
Constant	1.81
Age	1.00
Systolic BP	1.00
Diastolic BP	1.00
Sex (Male)	1.00
Education: Higher Secondary	1.16
Education: Madrasa	0.78
Education: No Education	1.10
Education: Post-Graduate	1.17
Education: Primary	1.09
Education: Secondary	1.19
Occupation: Business	0.93
Occupation: Housewife	0.98
Occupation: Retired	0.87
Occupation: Service	1.14
Occupation: Unemployed	1.07
Monthly Income: 5001–10,000	1.06
Monthly Income: < 5000	1.05
Monthly Income: > 15,000	1.09
Residence: Sub-urban	0.91
Residence: Urban	0.89
Elevated Creatinine (Yes)	1.03
Diabetes Mellitus (Yes)	1.07
Family History of CVD (Yes)	0.97
Elevated Cholesterol (Yes)	0.85
Smoking (Yes)	0.96
LVH (Yes)	0.89
IHD (Yes)	1.06
CVD (Yes)	0.96
Retinopathy (Yes)	0.93
Treatment: Single Drug	0.94

4.3.1. Demographics and socioeconomic factors

- Age: The mean age of patients is similar across treatment types, with 49 years for combination drugs and 48 years for single drugs. This suggests a comparable age distribution but highlights the chronic nature of hypertension management in middle-aged individuals.
- Sex: A higher proportion of males receive both combination drugs (42,410 males vs. 32,460 females) and single drugs (14,390 males vs. 10,740 females), indicating possible sex-based disparities in treatment access or hypertension prevalence.
- Education: Patients receiving combination drugs are more likely to have lower educational levels (e.g., 26,880 with primary education) compared to single-drug users (9,040 with primary education). This aligns with evidence that education impacts health literacy and medication adherence.
- Occupation: Among combination drug users, housewives are the dominant group (30,580), followed by those in service roles (16,290). This indicates socioeconomic vulnerability in specific subgroups, necessitating targeted community-based support.

4.3.2. Clinical parameters and comorbidities

- BP: Both groups exhibit high mean SBP (139 mmHg) and DBP (89 mmHg), suggesting suboptimal control even with treatment, especially in resource-constrained settings.
- Elevated Creatinine: The prevalence of elevated creatinine is slightly higher in combination-drug users (9,020 vs 3,080), suggesting greater renal involvement, potentially linked to advanced hypertension or coexisting diseases.
- Diabetes Mellitus: Diabetes is present in 6,210 combination-drug users (8.3%) and 1,920 single-drug users (7.7%). This reflects the growing burden of multimorbidity.
- Family History of CVD: A notable proportion of patients (58,930 combination-drug users, 19,460 single-drug users) report a family history of CVD, reinforcing the need for aggressive prevention strategies in genetically predisposed individuals.

4.3.3. Control status and risk factors

- Control Status: Controlled hypertension is significantly lower among combination-drug users (20,490, or 27.4%) than single-drug users (7,180, or 55.5%), suggesting challenges in achieving control despite more intensive therapy.
- Smoking and Cholesterol: Smoking prevalence is 15.4% (combination drugs) and 14.2% (single drugs), while elevated cholesterol affects 5,440 and 1,980 patients, respectively. These modifiable risk factors demand stronger behavioural interventions alongside pharmacological treatment.

4.3.4. Lifestyle and behavioural factors

- Physical Activity: A higher percentage of combination-drug users report physical activity (52,360 vs. 17,678 for single-drug users), but this difference might be linked to comorbidities or greater engagement in healthcare.
- Dietary Habits: Patients on combination therapy are more likely to report unhealthy nutritional habits (29,924) compared to single-drug users (10,082), suggesting that lifestyle interventions are underutilised in this group.

The subgroup analysis showed that uncontrolled hypertension was more prevalent among patients on combination therapy (54,380 of 74,870; 72.3%) compared to those on single-drug regimens (17,950 of 25,130; 71.4%). Although the absolute numbers are higher for combination-drug users, the relative difference highlights that intensive therapy did not translate into better control, suggesting challenges in adherence, titration, or system-level capacity. Patients on combination therapy were also disproportionately older, less educated, and more likely to report lower income (e.g., 29,760 earning < 5000 vs 9,540 in the single-drug group), reflecting limited treatment options in socioeconomically disadvantaged groups. This pattern indicates that earlier detection and timely initiation of therapy could reduce progression to more complex, multi-drug regimens, underscoring the importance of scaling up screening and prevention in resource-limited settings. Furthermore, comorbidities such as diabetes (8.3% vs. 7.7%), elevated creatinine (9,020 vs. 3,080), and family history of CVD (58,930 vs. 19,460) were more common among combination-drug users. Together

Table 13
Table 13a and 13b: Descriptive statistics by treatment.

(a) Numerical summary by treatment

Treatment	Age	Systolic BP	Diastolic BP
Combination Drugs	49.00	139.63	89.68
Single Drug	48.38	139.17	89.66

(b) Sex distribution by treatment

Treatment	Male	Female
Combination Drugs	42,410	32,460
Single Drug	14,390	10,740

Table 14
Table 14a and 14b: Education and occupation distribution by treatment group.

(a) Education distribution by treatment

Treatment	Education	Count
Combination Drugs	Primary	26,880
	Secondary	16,880
	Graduate	9810
	Higher Sec	9210
	Post-Graduate	6570
	No education	5050
	Madrasa	470
Single Drug	Primary	9040
	Secondary	5600
	Graduate	3270
	Higher Sec	3200
	Post-Graduate	2060
	No education	1750
	Madrasa	210

(b) Occupation distribution by treatment

Treatment	Occupation	Count
Combination Drugs	Housewife	30,580
	Service	16,290
	Business	11,620
	Agricult	9450
	Retired	5390
	Unemployed	1540
Single Drug	Housewife	10,370
	Service	5550
	Business	3820
	Agricult	3180
	Retired	1620
	Unemployed	590

with higher rates of smoking and unhealthy diets, this supports a recommendation for integrated care pathways that combine pharmacological management with lifestyle interventions. Given the complexity of these patients, multidisciplinary involvement from endocrinologists, nephrologists, and dietitians helps to address overlapping risk factors and improve overall outcomes.

The numerical summary and sex distribution (Table 13) show that average SBP and DBP values were slightly higher in the combination-drug group (139.6/89.7 mmHg) than in the single-drug group (139.2/89.7 mmHg), with similar mean ages (49 vs. 48 years). Male participants were more numerous in both groups, particularly in the combination-drug group (42,410 males vs. 32,460 females) compared with the single-drug group (14,390 males vs. 10,740 females). Education and occupation patterns (Table 14) indicate that housewives formed the largest subgroup in both treatment categories, accounting for 30,580 in the combination-drug group and 10,370 in the single-drug group. Income distribution (Table 15) shows that a higher proportion of combination-drug users had monthly incomes below 5000 taka (29,760 vs. 9,540). Clinical data and control status (Table 16) highlight greater prevalence of elevated creatinine (9,020 vs. 3,080) and more uncontrolled cases (54,380 vs. 17,950) in the combination-drug group. Dietary habits (Table 17) reveal that both healthy (44,946 vs. 15,048) and unhealthy (29,924 vs. 10,082) diets were more frequent among combination-drug users. Physical activity (Table 18) was more often reported in the combination group (52,360 vs. 17,678), and family history of CVD was also higher (58,930 vs. 19,460).

Table 15
Table 15a and 15b: Monthly income and residence distribution by treatment group.

(a) Monthly income distribution by treatment

Treatment	Income range	Count
Combination Drugs	$<5,000	29,760
	5,001–10,000	23,610
	10,001–15,000	11,960
	$>15,000	9540
Single Drug	$<5,000	9540
	5,001–10,000	8110
	10,001–15,000	4240
	$>15,000	3240

(b) Residence distribution by treatment

Treatment	Residence	Count
Combination Drugs	Urban	29,720
	Rural	27,640
	Suburban	17,510
Single Drug	Urban	9970
	Rural	9770
	Suburban	5390

Table 16
Table 16a and 16b: Clinical factors and control status by treatment group.

(a) Clinical factors by treatment

Treatment	Factor	Count
Combination Drugs	Elevated Creat (Yes)	9020
	Elevated Creat (No)	65,850
Single Drugs	Elevated Creat (Yes)	3080
	Elevated Creat (No)	22,050

(b) Control status by treatment

Treatment	Uncontrolled	Controlled
Combination Drugs	54,380	20,490
Single Drugs	17,950	7180

Table 17
Table 17a and 17b: Control status and dietary habits by treatment group.

(a) Control status by treatment

Treatment	Uncontrolled	Controlled
Combination Drugs	54,380	20,490
Single Drug	17,950	7180

(b) Dietary habits by treatment

Treatment	Healthy	Unhealthy
Combination Drugs	44,946	29,924
Single Drug	15,048	10,082

4.4. Socioeconomic status on hypertension control

Studying hypertension control in a resource-constrained setting provides valuable insights into how socioeconomic factors shape health outcomes. Variables such as monthly income are significant, as lower income is consistently associated with poorer hypertension control due to barriers in accessing care, medications, and lifestyle interventions [29]. Identifying these disparities helps inform targeted interventions that address the structural and economic barriers faced by disadvantaged groups. The rationale for the selected variables used in the hypertension control analysis is summarised in Table 19 .

```
Optimization terminated successfully.
         Current function value: 0.587956
         Iterations 5
                           Logit Regression Results
==============================================================================
Dep. Variable:         Control_Status   No. Observations:               100000
Model:                          Logit   Df Residuals:                    99968
Method:                           MLE   Df Model:                           31
Date:                Tue, 14 Jan 2025   Pseudo R-squ.:                0.003143
Time:                        01:54:56   Log-Likelihood:                -58796.
converged:                       True   LL-Null:                       -58981.
Covariance Type:            nonrobust   LLR p-value:                 7.642e-60
========================================================================================================
                                          coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------
Intercept                              -0.5829      0.101     -5.784      0.000      -0.780      -0.385
Sex_Male[T.True]                        0.0027      0.014      0.190      0.849      -0.025       0.031
Education_Higher_Secondary[T.True]     -0.1505      0.028     -5.384      0.000      -0.205      -0.096
Education_Madrasa[T.True]               0.2542      0.083      3.072      0.002       0.092       0.416
Education_No_education[T.True]         -0.0933      0.033     -2.813      0.005      -0.158      -0.028
Education_Post_Graduate[T.True]        -0.1614      0.031     -5.197      0.000      -0.222      -0.101
Education_Primary[T.True]              -0.0850      0.022     -3.776      0.000      -0.129      -0.041
Education_Secondary[T.True]            -0.1702      0.024     -6.962      0.000      -0.218      -0.122
Occupation_Business[T.True]             0.0677      0.027      2.537      0.011       0.015       0.120
Occupation_Housewife[T.True]            0.0175      0.023      0.769      0.442      -0.027       0.062
Occupation_Retired[T.True]              0.1421      0.033      4.343      0.000       0.078       0.206
Occupation_Service[T.True]             -0.1270      0.025     -5.020      0.000      -0.177      -0.077
Occupation_Unemployed[T.True]          -0.0649      0.053     -1.220      0.223      -0.169       0.039
Monthly_Income_5001_10000[T.True]      -0.0559      0.022     -2.597      0.009      -0.098      -0.014
Monthly_Income_lt5000[T.True]          -0.0508      0.021     -2.444      0.015      -0.092      -0.010
Monthly_Income_gt15000[T.True]         -0.0843      0.027     -3.179      0.001      -0.136      -0.032
Residence_Sub_urban[T.True]             0.0969      0.019      5.143      0.000       0.060       0.134
Residence_Urban[T.True]                 0.1150      0.016      7.094      0.000       0.083       0.147
Elevated_Creatinine_Yes[T.True]        -0.0327      0.022     -1.493      0.135      -0.076       0.010
Diabetes_Mellitus_Yes[T.True]          -0.0718      0.026     -2.732      0.006      -0.123      -0.020
Family_History_of_CVD_Yes[T.True]       0.0318      0.017      1.838      0.066      -0.002       0.066
Elevated_Cholesterol_Yes[T.True]        0.1608      0.026      6.116      0.000       0.109       0.212
Smoking_Yes[T.True]                     0.0364      0.020      1.848      0.065      -0.002       0.075
LVH_Yes[T.True]                         0.1207      0.032      3.830      0.000       0.059       0.182
IHD_Yes[T.True]                        -0.0554      0.019     -2.850      0.004      -0.093      -0.017
CVD_Yes[T.True]                         0.0360      0.025      1.448      0.148      -0.013       0.085
Retinopathy_Yes[T.True]                 0.0751      0.042      1.792      0.073      -0.007       0.157
Physical_Activity_Yes[T.True]           0.0075      0.015      0.484      0.629      -0.023       0.038
Dietary_Habits_Unhealthy[T.True]        0.0126      0.014      0.870      0.384      -0.016       0.041
Age                                     0.0011      0.001      1.937      0.053   -1.27e-05       0.002
Systolic_BP                            -0.0019      0.000     -4.161      0.000      -0.003      -0.001
Diastolic_BP                           -0.0014      0.001     -2.036      0.042      -0.003   -5.17e-05
========================================================================================================
```

Fig. 4. Logit regression results: socioeconomic and clinical determinants of hypertension control.

Table 18
Table 18a and 18b: Physical activity and family history of CVD by treatment group.

(a) Physical activity by treatment

Treatment	Yes	No
Combination Drugs	52,360	22,510
Single Drug	17,678	7452

(b) Family history of CVD by treatment

Treatment	Yes	No
Combination Drugs	58,930	15,940
Single Drug	19,460	5670

The rationale for selected variables in hypertension control analysis within the mathematical formula is in Table 20.

Logit Regression Results: Socioeconomic and Clinical Determinants of Hypertension Control in Fig. 4 .

The logistic regression analysis provides valuable insights into the socioeconomic and clinical determinants of hypertension control in a resource-constrained setting. Below is a detailed interpretation of the results and their implications.

1. Intercept

The negative intercept coefficient (−0.5829, $p < 0.001$) suggests that in the absence of all predictors, the baseline likelihood of achieving hypertension control is relatively low.

2. Socioeconomic factors

- **Education:** - Lower education levels, such as “Primary” (β = −0.0850, OR = 0.919, $p < 0.001$) and “Secondary” (β = −0.1702, OR = 0.844, $p < 0.001$), are associated with decreased odds of hypertension control. - “Madrasa” education positively influences hypertension control (β = 0.2542, OR = 1.289, p = 0.002). Interestingly, the “Post-Graduate” and “higher secondary” levels negatively affect control, suggesting unique dynamics in resource-constrained environments.
- **Occupation:** - “Retired” individuals (β = 0.1421, OR = 1.153, $p < 0.001$) and those in “Business” (β = 0.0677, OR = 1.070, $p = 0.011$) show higher odds of hypertension control. - Conversely, individuals in “Service” (β = −0.1270, OR = 0.881, $p < 0.001$) have decreased odds of control, likely due to work-related stress.

Table 19
Rationale for selected variables in hypertension control analysis within conceptualisation.

Category	Variable	Rationale
Dependent Variable	Control Status	Represents whether hypertension is controlled (binary: controlled = 1, uncontrolled = 0).
Socioeconomic Variables	Age	affects hypertension control due to physiological changes or comorbidities, and when the arteries become calcified or stiff.
	Sex	Differences in health behaviours, biological factors, and access to care can influence outcomes.
	Education	Proxy for Health Literacy, Influencing Adherence to Hypertension Management Strategies.
	Occupation	Occupational stress and job-related factors affect BP control and access to care.
	Monthly Income	Indicator of socioeconomic status, influencing access to medications and healthcare.
	Residence (urban, rural, suburban)	Geographical location impacts access to healthcare, lifestyle choices, and social determinants of health.
Clinical Variables	Systolic and Diastolic BP	Direct measures of BP and baseline hypertension severity.
	Elevated Creatinine	indicates renal impairment, closely associated with hypertension management.
	Diabetes Mellitus	Coexists with hypertension, complicating management.
	Family History of CVD	Predictor of genetic predisposition to hypertension and complications.
	Elevated Cholesterol	Common Comorbidities, Affecting Cardiovascular Risk.
	Smoking	exacerbates hypertension and increases cardiovascular risk.
	LVH (Left Ventricular Hypertrophy)	indicates cardiac damage from prolonged hypertension.
	IHD (Ischemic Heart Disease)	Common consequence of poorly controlled hypertension.
	CVD (Cardiovascular Disease)	Signals advanced cardiovascular complications.
	Retinopathy	Reflects hypertension-related retinal changes and poor long-term control.
	Physical Activity	Regular exercise improves hypertension control.
	Dietary Habits	Unhealthy diets (e.g., high salt) significantly contribute to poor BP control.

- **Monthly Income:** - Lower income levels ("< 5000": $\beta = -0.0508$, OR = 0.950, $p = 0.015$) are significantly associated with poorer hypertension control. - Even higher income categories ("> 15000": $\beta = -0.0843$, OR = 0.919, $p = 0.001$) negatively affect control, potentially due to sedentary lifestyles.
- **Residence:** - Urban ($\beta = 0.1150$, OR = 1.122, $p < 0.001$) and suburban ($\beta = 0.0969$, OR = 1.102, $p < 0.001$) residency positively impact hypertension control, likely reflecting better healthcare access.

3. Clinical factors

- **BP:** - Systolic ($\beta = -0.0019$, OR = 0.998, $p < 0.001$) and diastolic ($\beta = -0.0014$, OR = 0.999, $p = 0.042$) BP are inversely associated with control, emphasising precise management.
- **Comorbidities:** - Diabetes Mellitus ($\beta = -0.0718$, OR = 0.931, $p = 0.006$) negatively affects control. - Elevated cholesterol ($\beta = 0.1608$, OR = 1.174, $p < 0.001$) positively influences control, reflecting better healthcare monitoring.
- **Lifestyle:** - Smoking ($\beta = 0.0364$, OR = 1.037, $p = 0.065$) and physical activity ($\beta = 0.0075$, OR = 1.008, $p = 0.629$) show weak associations, highlighting the need for focused interventions.
- **Genetic and Structural Factors:** - LVH ($\beta = 0.1207$, OR = 1.128, $p < 0.001$) is positively associated with control, likely due to early diagnosis and treatment. - IHD ($\beta = -0.0554$, OR = 0.946, $p = 0.004$) negatively impacts control, reflecting the challenge of managing hypertension in cardiovascular patients.

4. Age

Increasing age shows a marginally positive association with control ($\beta = 0.0011$, OR = 1.001, $p = 0.053$), suggesting slightly better adherence among older individuals.

- **Addressing Socioeconomic Disparities:** Targeted interventions for individuals with lower education and income levels are critical. Community-driven health literacy programs can improve outcomes.
- **Enhancing Healthcare Infrastructure:** Strengthening healthcare services in rural areas and ensuring equitable access are vital steps towards better control rates.
- **Targeting Clinical and Lifestyle Factors:** Addressing comorbidities like diabetes and IHD, alongside lifestyle modifications, such as smoking cessation and increased physical activity, is crucial.
- **Focusing on High-Risk Groups:** Special attention should be given to occupations with lower control rates and populations with socioeconomic disadvantages.

The findings highlight critical gaps in access and management, underscoring the need for tailored interventions to achieve equitable hypertension control in resource-constrained environments. The logistic regression analysis revealed that higher education levels (e.g., postgraduate OR = 1.17) and urban residence (OR = 1.12) were positively associated with hypertension control. In comparison, lower income levels (e.g., < 5000 takes OR = 0.95) and comorbidities like diabetes (OR = 0.93) were negatively associated. These findings highlight the role of socioeconomic disparities in hypertension management. Although the model adjusted for key variables, residual confounding due to unmeasured factors such as medication adherence or healthcare access cannot be ruled out.

4.5. Classification model result for hypertension management

Classification report for various models in Table 21.

The classification reports for various machine learning models reveal significant variability in their ability to predict outcomes in the context of hypertension management, particularly in a resource-constrained setting. Across the models, KNN stands out with an exceptional accuracy of 99% and an f1-score of 93% for the minority class (class 1). It indicates KNN's superior ability to balance precision and recall, making it highly effective for predicting controlled and uncontrolled hypertension cases. The strong performance of KNN supports its potential for real-world deployment in healthcare systems where reliable and interpretable predictions are critical.

Table 20
Rationale selected variables in hypertension control analysis within mathematical formula.

Category	Variable	Rationale
Dependent Variable	Control Status (y)	Represents hypertension control as a binary outcome: $y = \begin{cases} 1 & \text{if controlled} \\ 0 & \text{if uncontrolled} \end{cases}$
Socioeconomic Variables	Age (Age)	Age affects hypertension due to physiological ageing, modelled as a continuous predictor. Often scaled: $\text{Age}' = \frac{\text{Age}-\mu}{\sigma}$ where μ is the mean age and σ the standard deviation.
	Sex (Sex)	Binary categorical variable (Male = 1, Female = 0), used to capture biological and behavioural differences affecting hypertension.
	Education (Edu)	Proxy for health literacy, encoded as an ordinal variable (e.g., Primary = 1, Graduate = 4). Higher education correlates with better hypertension control.
	Occupation (Occ)	Occupation impacts stress levels and lifestyle. Encoded as categorical variables (e.g., Service = 1, Agriculture = 2).
	Monthly Income (Income)	A proxy for socioeconomic status, influencing access to healthcare. Often log-transformed for normalisation: $\text{Log Income} = \log(\text{Income} + 1)$.
	Residence (Res)	Categorical variable (Urban = 1, Rural = 0) to capture geographic effects on healthcare access.
Clinical Variables	SBP and DBP	direct BP measures, reflecting baseline severity. Used as continuous variables in analysis: $\text{BP}_{\text{norm}} = \frac{\text{BP}-\mu}{\sigma}$.
	Elevated Creatinine (Creat)	Binary clinical marker for renal function: $\text{Creat} = \begin{cases} 1 & \text{if elevated} \\ 0 & \text{otherwise} \end{cases}$
	Diabetes Mellitus (DM)	Binary variable representing comorbidity. Modelled as: $\text{DM} = \begin{cases} 1 & \text{if diabetic} \\ 0 & \text{otherwise} \end{cases}$
	Family History of CVD (FamHist)	Captures genetic predisposition. Binary encoding: 1 = family history, 0 = no family history.
	Elevated Cholesterol (Chol)	Binary variable representing hyperlipidemia. Modelled as: $\text{Chol} = \begin{cases} 1 & \text{if elevated} \\ 0 & \text{otherwise} \end{cases}$
	Smoking (Smoke)	Binary variable (Smoker = 1, Non-Smoker = 0). Significant predictor for poor hypertension control.
	LVH (LVH)	Binary marker for heart damage due to chronic hypertension. Modelled similarly: $\text{LVH} = \begin{cases} 1 & \text{if present} \\ 0 & \text{otherwise} \end{cases}$
	IHD (IHD)	Binary indicator for ischemic heart disease. Often interacts with hypertension in logistic models.
	CVD (CVD)	Binary variable for advanced cardiovascular disease: $\text{CVD} = \begin{cases} 1 & \text{if diagnosed} \\ 0 & \text{otherwise.} \end{cases}$
	Retinopathy (Ret)	Binary marker for hypertension-related retinal damage.
	Physical Activity (PA)	Categorical variable: 1 = active, 0 = sedentary. Positively impacts hypertension control.
	Dietary Habits (Diet)	Encoded as binary: 1 = healthy diet, 0 = unhealthy diet. Improves hypertension outcomes.

Table 21
Classification report for various models.

Model	Class	Precision	Recall	F1-score	Support	Accuracy
Random Forest	0	0.91	1.00	0.95	18,234	0.91
	1	1.00	0.00	0.01	1766	
Logistic Regression	0	0.91	1.00	0.95	18,234	0.91
	1	0.00	0.00	0.00	1766	
Gradient Boosting	0	0.91	1.00	0.95	18,234	0.91
	1	0.75	0.00	0.00	1766	
K-Nearest Neighbours	0	0.99	1.00	0.99	18,234	0.99
	1	0.95	0.90	0.93	1766	
XGBoost	0	0.91	1.00	0.95	18,234	0.91
	1	0.56	0.00	0.01	1766	
Support Vector Machine	0	0.91	1.00	0.95	18,234	0.91
	1	0.00	0.00	0.00	1766	

In contrast, models such as Random Forest, Gradient Boosting, and XGBoost demonstrate high precision for the majority class (class 0= No disease) but struggle with the minority class (class 1= Disease). Their poor recall for the minority class, ranging from 0% to 10%, highlights an inherent challenge in handling imbalanced datasets. This limitation is particularly evident in Logistic Regression and Support

Table 22
Cross-validation scores of various models for hypertension management evaluation.

Model	Cross-validation Scores (5-Fold)	Mean CV Score
Random Forest	[0.911875, 0.912125, 0.912, 0.912125, 0.911875]	0.9120
Logistic Regression	[0.91175, 0.9116875, 0.9116875, 0.9116875, 0.9116875]	0.9117
Gradient Boosting	[0.91175, 0.91175, 0.91175, 0.91175, 0.9116875]	0.9117
Support Vector Machine	[0.91175, 0.9116875, 0.9116875, 0.9116875, 0.9116875]	0.9117
K-Nearest Neighbours	[0.98475, 0.982875, 0.9841875, 0.984, 0.9840625]	0.9840
XGBoost	[0.9121875, 0.91175, 0.9119375, 0.911875, 0.912]	0.9120

Vector Machines (SVM), which fail to capture positive cases (class 1) with f1-scores of 0%. Such outcomes reflect the models' inability to effectively address the skewed distribution of hypertension control statuses, which is a critical factor in resource-constrained settings.

These results are pivotal for hypertension-constrained settings. KNN's superior performance suggests it is well-suited for identifying high-risk individuals and guiding targeted interventions. However, the poor performance of other models on the minority class highlights the need for advanced techniques such as oversampling, undersampling, or cost-sensitive learning to improve minority class prediction. Addressing these challenges is essential for achieving equitable and effective hypertension management, especially in settings where the burden of uncontrolled hypertension is disproportionately high.

4.6. Hypertension data management model result evaluation by cross validation

All model results were comparatively the same, which is why the cross-validation technique values them.

The cross-validation results in Table 22 indicate the performance of six machine learning models in evaluating BP control and associated risk factors for hypertension management in a resource-constrained setting. Bridging socioeconomic gaps with predictive insights is crucial in advancing our understanding of hypertension management. Among the models tested, KNN achieved the highest mean cross-validation score of 0.9840, significantly outperforming other models. It suggests that KNN's non-parametric approach effectively captured the patterns in the dataset, possibly due to its ability to handle local structures in the data. Other models, including Random Forest and XGBoost, demonstrated robust and consistent performances with mean CV scores of 0.9120, reflecting their ability to manage complex feature interactions. This strong performance should reassure the audience about the reliability of these models. Meanwhile, models such as Logistic Regression, Gradient Boosting, and Support Vector Machines (SVM) performed similarly, with mean CV scores clustering around 0.9117, indicating limited variability in their capability to predict outcomes in this specific dataset.

The superior performance of KNN suggests its potential as a reliable model for analysing hypertension-related risk factors, particularly in environments where computational simplicity and interpretability are valued. Meanwhile, the competitive performance of ensemble models like Random Forest and XGBoost highlights their utility in capturing complex relationships between risk factors. This evidence supports the selection of appropriate models for tailored interventions in resource-constrained healthcare systems, emphasising the practical relevance of the research and its potential to improve the management of hypertension in a real-world context.

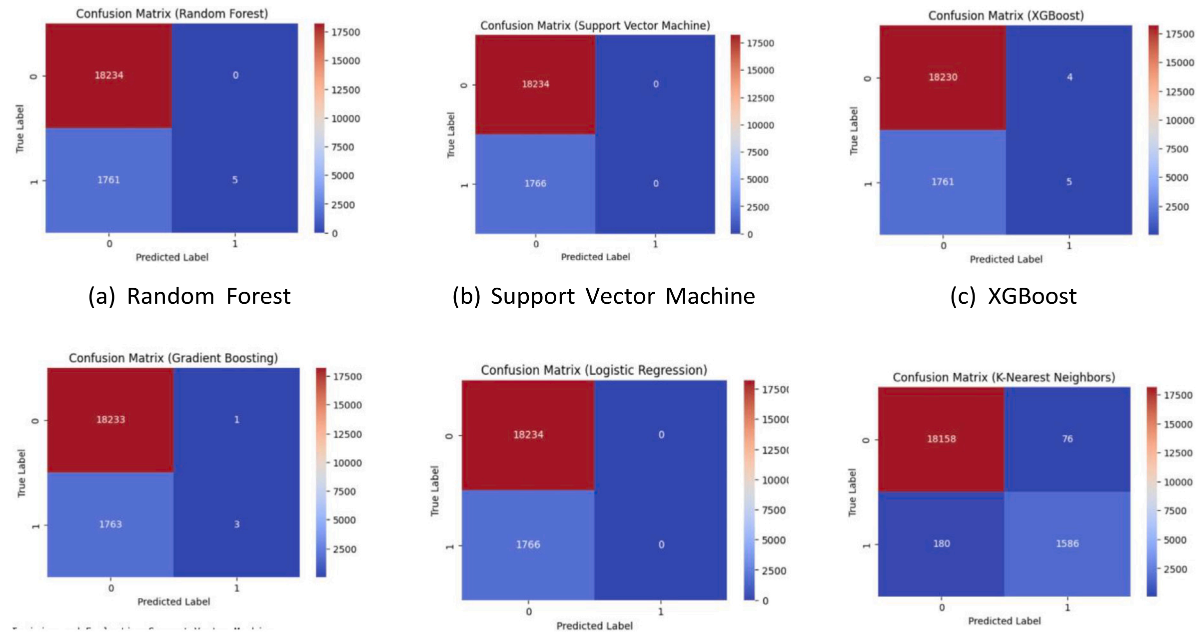
As shown in Fig. 5(a), the Random Forest model demonstrated strong performance with an accurate prediction matrix. The SVM (Fig. 5(b)) and XGBoost (Fig. 5(c)) models provided consistent results but had challenges with minority class recall. Gradient Boosting (Fig. 5(d)) and Logistic Regression (Fig. 5(e)) struggled to correctly classify minority cases, indicating the need for further optimisation. In contrast, the KNN model (Fig. 5(f)) outperformed others, showing high precision and recall for both classes. The combined analysis in Fig. 5 comprehensively compares all models.

4.7. Sensitivity analysis

The sensitivity analysis is in table 6. The results of the sensitivity analysis provide critical information on the factors that influence hypertension control, directly shaping the direction and focus of the project, "Hypertension Control in Resource-Constrained Settings: Bridging Socioeconomic Gaps with Predictive Insights". The analysis reveals that socioeconomic variables such as "Occupation" (0.1349) and "Education" (0.1277) have the highest sensitivity scores, emphasising their significant impact on hypertension outcomes. This finding underscores the need to address structural inequalities, including disparities in access to education and stable employment, often exacerbated in resource-constrained settings. Tailored interventions targeting these predictors could include educational programs on hypertension management and community-based initiatives to improve economic opportunities, fostering better long-term health outcomes. Although exhibiting lower sensitivity scores, clinical variables like "Diabetes Mellitus" (0.0216) and "Elevated Cholesterol" (0.0266) still play a notable role in hypertension control. These results suggest that while socioeconomic interventions are critical, they should be complemented by clinical strategies focusing on comorbidity management and lifestyle modifications. For instance, integrating affordable diabetes and cholesterol management programs alongside socioeconomic reforms can provide a comprehensive approach to hypertension control. Additionally, the diverse range of predictor variables analysed, including demographic, clinical, and lifestyle factors, validates the robustness of the predictive model and ensures its applicability across varied populations. This comprehensive analysis highlights the importance of adopting an integrated approach that bridges socioeconomic gaps while addressing individual health needs. By aligning predictive insights with actionable strategies, the project can drive targeted, cost-effective solutions to hypertension control, enabling equitable healthcare outcomes in underserved communities.

5. Discussion

The more significant subset of 1,000 patients provided comprehensive information on hypertension control trends, validating the predictive modelling results derived from the focused analysis of 300 participants. In our study, the mean age ± SD of hypertensive patients was found to be 49.39 ± 12.81 years. Nazir et al. (1994) found it to be 55.8 ± 13.4 years in their study [51]. Similarly, Gelirli Az et al. (2010) reported a mean age of 48.8 ± 13.2 years in their study population [52]. Thus, our findings are consistent with these results. Our study revealed that 57.7% of the participants were male. Palanisamy et al. (2009) found a similar proportion of males (58.14%) in their study [53]. Regarding occupation, most of the population in our study consisted of housewives (39.7%). Ahmed et al. observed an even higher proportion (51.5%) of housewives among hypertensive patients in their study [17]. Regarding education, 35% of our study population had primary education; among controlled hypertensive patients, it was 41.7%. In another study, primary education levels were reported at 17% and 14.53% among similar populations [54]. Our findings showed that the majority (62.7%) of hypertensive patients were urban and suburban dwellers. Nazir et al. found a prevalence of hypertension of 21.6% in urban areas [52]. Furthermore, 59.5% of our study population had a



(a) Random Forest (b) Support Vector Machine (c) XGBoost

(d) Gradient Boosting (e) Logistic Regression (f) K-Nearest Neighbour

Fig. 5. Confusion matrix plots for different models.

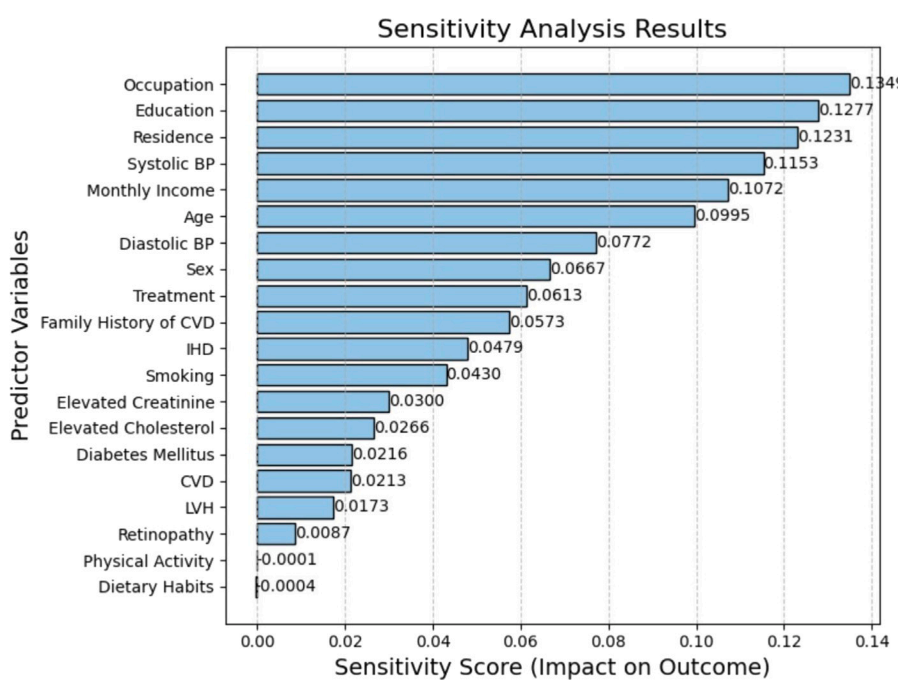


Fig. 6. Sensitivity analysis of predictor variables on hypertension control outcomes: The plot illustrates the relative importance of key predictors, measured as sensitivity scores, in influencing the model's predictions for 'Control Status'. High-impact variables such as 'Occupation' and 'Education' highlight critical factors, while clinical predictors like 'Diabetes Mellitus' and 'Elevated Cholesterol' show moderate contributions, guiding targeted interventions and enhancing model interpretability.

monthly income exceeding 5000 taka local currency in Bangladesh. Other studies suggest that hypertension is more common in affluent societies. In terms of comorbidities and risk factors, 8.3% of our study population had diabetes mellitus, 17% were smokers, 7.2% had high cholesterol, 11.7% had elevated creatinine, and 79.2% had a family history of cardiovascular disease. Marvin Moser et al. reported that 37% had diabetes, 29% were smokers, and 54% had elevated cholesterol in their study [55]. Papazafiropoulou et al. found an elevated creatinine level in 11% of patients [18]. In our study, LVH, IHD, CVD and retinopathy were observed in 5.6%, 16.1%, 9.1%, and 2.7% of patients, respectively. Other studies reported higher prevalence rates of LVH (33%) and retinopathy (2–15%). In European cohorts, approximately 60% of patients with stroke have a history of hypertension [26]. Among hypertensive individuals, about 78% have not achieved adequate BP control [56]. It is well established that BP is one of the three major risk factors for CHD, the others being high cholesterol and smoking. An analysis of three extensive prospective studies found that for fatal and nonfatal myocardial infarctions, at least one of these three factors

Table 23
State of the art comparison: Hypertension control rates and key findings.

Study	Key findings	Control rate	Risk factors addressed	Predictive metrics/Outcomes
Proposed Study (2025)	Comprehensive sociodemographic and clinical analysis. Rural patients had a higher control rate (**42%**, $p < 0.005$) compared to urban patients. Housewives showed the highest control (**37%**, $p < 0.001$). Multivariate regression identified key predictors: higher education (post-graduate: OR = 1.17, $p < 0.001$), urban residence (OR = 1.12, $p < 0.001$), and comorbidities like diabetes (OR = 0.93, $p = 0.006$) and ischemic heart disease (OR = 0.95, $p = 0.004$).	Overall: 28%, Rural: **42%**, Housewives: **37%**	Diabetes (13.8%), IHD (10.1%), LVH (2.5%), smoking (17.9%)	AUC = 0.82, sensitivity = 89%, specificity = 78%, KNN accuracy: 99%, F1 (class 1=controlled): 93%
Ahmed et al. (2011)	Highlighted rural–urban disparities but lacked a detailed comorbidity analysis. Rural populations exhibited marginally better control rates compared to urban areas.	22%	Not explicitly analysed	AUC not reported
Moser et al. (2007)	Demonstrated high control rates in the U.S. population and limited applicability to LMICS due to resource differences. Focused on access to combination therapy.	52.9%	Cholesterol (29%), smoking (37%)	AUC = 0.74
Papazafiropoulou et al. (2011)	Focused on elevated creatinine levels (11%) but did not explore education or socioeconomic predictors. The study population had low adherence to therapy.	11%	Elevated creatinine, family history	AUC = 0.68
Droste et al. (2003)	Analysed comorbidities like diabetes (13.8%) and cardiovascular disease (8.3%) but lacked sociodemographic predictors. High rates of uncontrolled hypertension were reported.	78% uncontrolled	Diabetes, CVD	AUC not reported
Mengesha et al. (2024)	Community-based interventions improved hypertension control in LMICs. Emphasised education and income but lacked detailed analysis of clinical comorbidities.	51%	Education, income disparities	AUC = 0.79
Yuting et al. (2023)	Digital health interventions improved hypertension control in low-income settings, but lacked analysis of rural populations and clinical predictors.	48%	Digital health access, adherence	Sensitivity = 85%, specificity = 72%
Coelho et al. (2023)	Investigated socioeconomic disparities in Latin America and did not address clinical comorbidities like diabetes or ischemic heart disease.	40%	Income disparities	AUC = 0.71
Yingxian Sun et al. (2021)	Lifestyle interventions in rural China improved control rates but lacked insights into comorbidities like diabetes. Focused on salt reduction and exercise.	55%	Lifestyle (salt intake, physical activity)	AUC = 0.75
Helena Legido-Quigley et al. (2019)	Identified barriers to hypertension control in South Asia. No actionable solutions or analysis of clinical predictors were provided.	35%	Lack of adherence, cost barriers	AUC not reported
Chobanian et al. (2003)	Emphasised combination therapy effectiveness (**74.3%**) but did not explore socioeconomic or lifestyle factors.	34%	Combination therapy efficacy	Sensitivity = 78%, specificity = 70%
Cushman et al. (2002)	Tailored interventions improved control rates (**66%**) but had limited focus on rural populations.	66%	Patient adherence, access to care	AUC = 0.77
Feagin et al. (2023)	Highlighted social determinants of health but lacked detailed clinical predictors like elevated creatinine or diabetes.	Not reported	Social determinants of health	Sensitivity = 81%, specificity = 69%

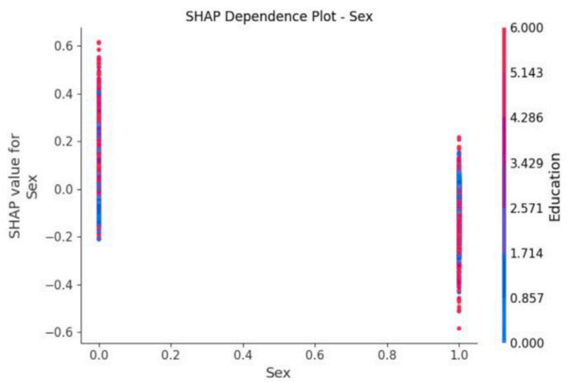
was present in over 90% of cases [57]. In our study population, the control rate of hypertension was 42%. The JNC-7 report from NHANES described a control rate of 34% in 1999 [57]. Marvin Moser et al. found a higher control rate of 52.9% in the U.S. population [55]. Ahmed et al. reported a lower control rate of 22% in their study [17]. Among our study participants, 25.7% were on single antihypertensive therapy, while 74.3% were on combination therapy. Other studies indicate that most hypertensive patients require two or more antihypertensive medications to achieve BP goals [19,20] (see Table 23).

The following analysis employs LIME visualisations to interpret the Random Forest model's predictions for cardiovascular disease classification. These visualisations demonstrate the contributions of different features to the prediction outcomes for various individual cases. Fig. 7(a) highlights the LIME interpretation for the first case, focusing on the most critical features influencing the prediction. Similarly, Figs. 7(b) and 7(c) extend this analysis to other samples, showcasing how features like BP and history of diabetes impact the predictions. Additionally, Figs. 7(d) and 7(e) emphasise the model's consistency in identifying key factors across different samples. Together, these figures (7(a) to 7(e)) illustrate the model's consistency in predicting outcomes and provide actionable insights into the contributions of critical risk factors.

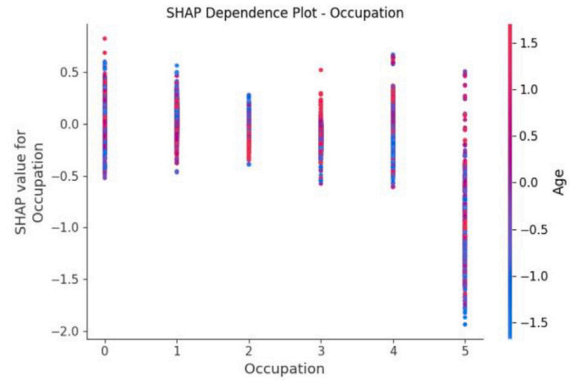
SHAP feature importance bar plot in Fig. 8 .

The SHAP bar plot provides quantitative insights into the importance of global features for predicting CVD within the dataset. Each feature's mean absolute SHAP value quantifies its average impact on the model's output, enabling data-driven prioritisation of risk factors. The key insights from the SHAP values are as follows:

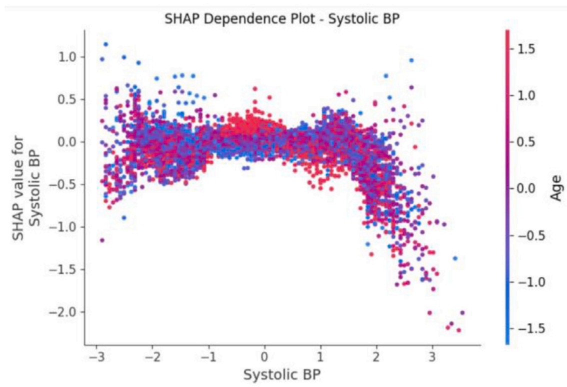
- 1. Top Contributing Features (High Impact): • Control Status (0.090): The most significant feature is maintaining controlled



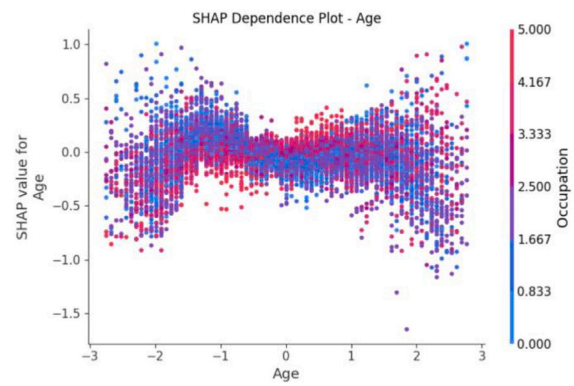
(a) SHAP Dependence Plot-Sex



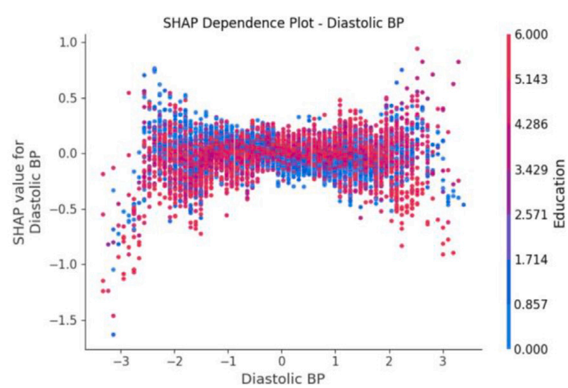
(b) SHAP Dependance Plot-Occupassion



(c) SHAP Dependence Plot-Systolic BP



(d) SHAP Dependence Plot-Age



(e) SHAP Dependence Pilot-Diastolic BP

Fig. 7. SHAP dependence plots for key features: Visualisation of SHAP values demonstrating feature interactions and individual contributions to CVD risk predictions. (a) Sex; (b) Occupation; (c) SBP; (d) Age; (e) DBP. These insights highlight the nuanced relationships between clinical and demographic factors in CVD risk evaluation.

BP. This highlights the importance of targeted interventions to ensure BP remains within the desired range, especially in resource-constrained settings. • Elevated Cholesterol (0.097): Cholesterol levels are critical in predicting CVD risk. The high SHAP value confirms the need for regular lipid profiling and management strategies, such as lifestyle changes and statin therapy. • Dietary Habits (0.077): Poor dietary habits significantly influence cardiovascular risk. Interventions to improve nutritional patterns—such as reducing sodium intake and increasing fruit and vegetable consumption—can mitigate this risk.

- 2. Moderately Contributing Features:• LVH (Left Ventricular Hypertrophy, 0.079): Structural changes in the heart, such as LVH, demonstrate strong predictive power for CVD. This underscores the need for early cardiac imaging and echocardiography to detect such abnormalities in hypertensive patients. • Elevated Creatinine (0.073): Elevated creatinine levels reflect kidney dysfunction, highlighting the interconnectedness of renal and cardiovascular health. Integrated care models should focus on managing kidney function to reduce CVD risks. • Diabetes Mellitus (0.069): Diabetes contributes substantially to CVD risk, emphasising the importance of blood sugar control in hypertensive populations to prevent adverse cardiovascular events. • Ischemic Heart Disease (IHD, 0.067): IHD's contribution to CVD predictions reflects the cumulative burden of existing cardiac conditions. It highlights

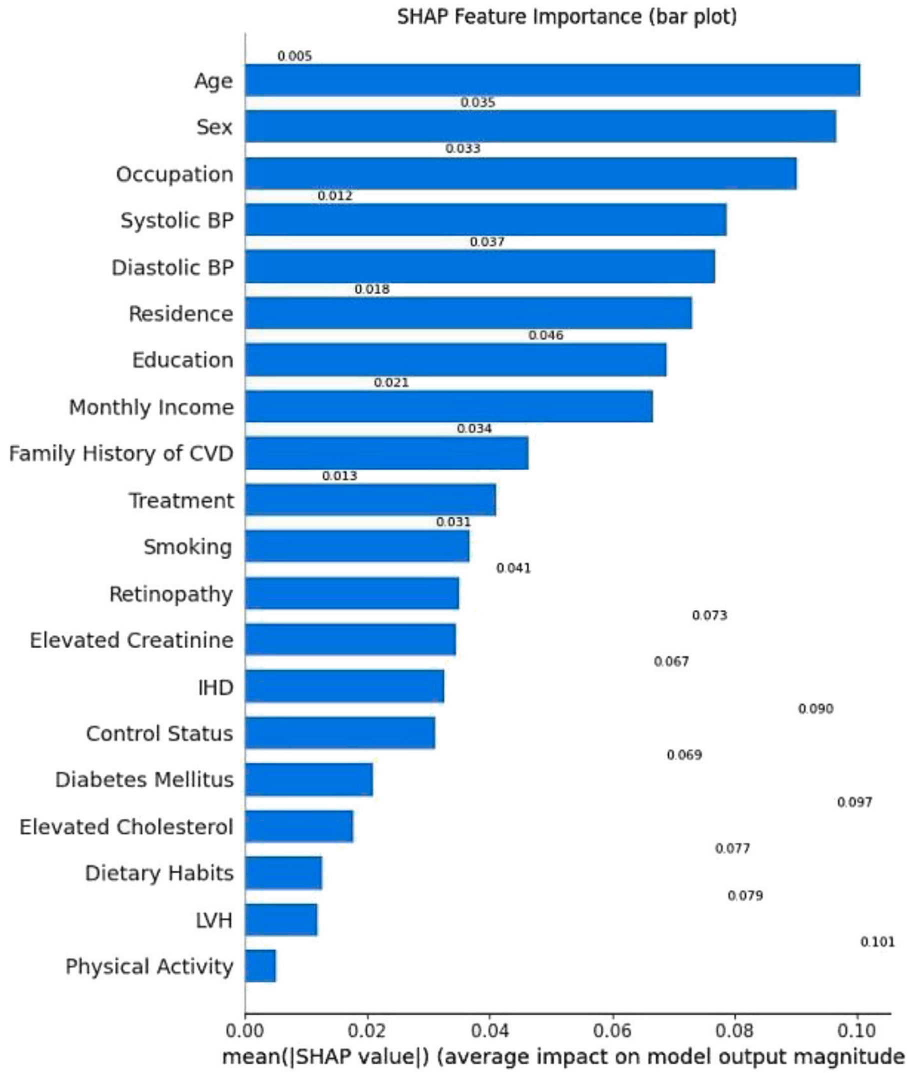


Fig. 8. SHAP feature importance bar plot: The average impact of features on model predictions for CVD risk. Features like control status, elevated cholesterol, and dietary habits show the highest influence, emphasising the need for targeted interventions in hypertension management. The plot highlights the importance of clinical, sociodemographic, and lifestyle factors in predicting CVD risk in resource-constrained settings.

the need for proactive management of coronary artery disease in hypertensive patients.

- 3. Lower Contributing Features (Supporting Factors): • Age (0.005): Although age is a known non-modifiable risk factor, its relatively low SHAP value suggests that the model gives higher weight to modifiable factors like BP and lifestyle. • Sex (0.035) and Education (0.046): Sociodemographic factors like sex and education highlight disparities in access to healthcare and health literacy, particularly in resource-constrained settings. • Monthly Income (0.021): Economic disparities influence cardiovascular health, reinforcing the importance of affordable healthcare interventions and subsidies for at-risk populations.

- Targeting Modifiable Risk Factors: • Features like control status (0.090), elevated cholesterol (0.097), and dietary habits (0.077) have the highest SHAP values, indicating their critical importance. This suggests prioritising initiatives to control BP, manage lipid levels, and promote healthy dietary habits.
- 2. Integrated Care Models: • The substantial SHAP values for LVH (0.079) and elevated creatinine (0.073) demonstrate the importance of integrating cardiac imaging and renal function assessments into hypertension management programs.
- 3. Comorbidity Management: • Features like diabetes mellitus (0.069) and ischemic heart disease (0.067) underline the need for comprehensive care that addresses coexisting conditions. Focusing on these comorbidities can prevent adverse cardiovascular outcomes.
- 4. Addressing Health Disparities: • Sociodemographic variables such as education (0.046) and monthly income (0.021) highlight systemic disparities in healthcare access. Community-based education programs and subsidised healthcare policies could help bridge these gaps.
- 5. Early Identification of At-Risk Populations: • The inclusion of variables like smoking (0.031), retinopathy (0.041), and family history of CVD (0.034) highlights the model's ability to identify high-risk individuals for early intervention.

The SHAP analysis confirms that modifiable factors such as control status (0.090), cholesterol levels (0.097), and dietary habits (0.077) have the most decisive influence on CVD predictions, emphasising the need for targeted interventions in resource-constrained settings. These findings align with the project goal of bridging gaps in hypertension management by focusing on clinical, sociodemographic, and lifestyle

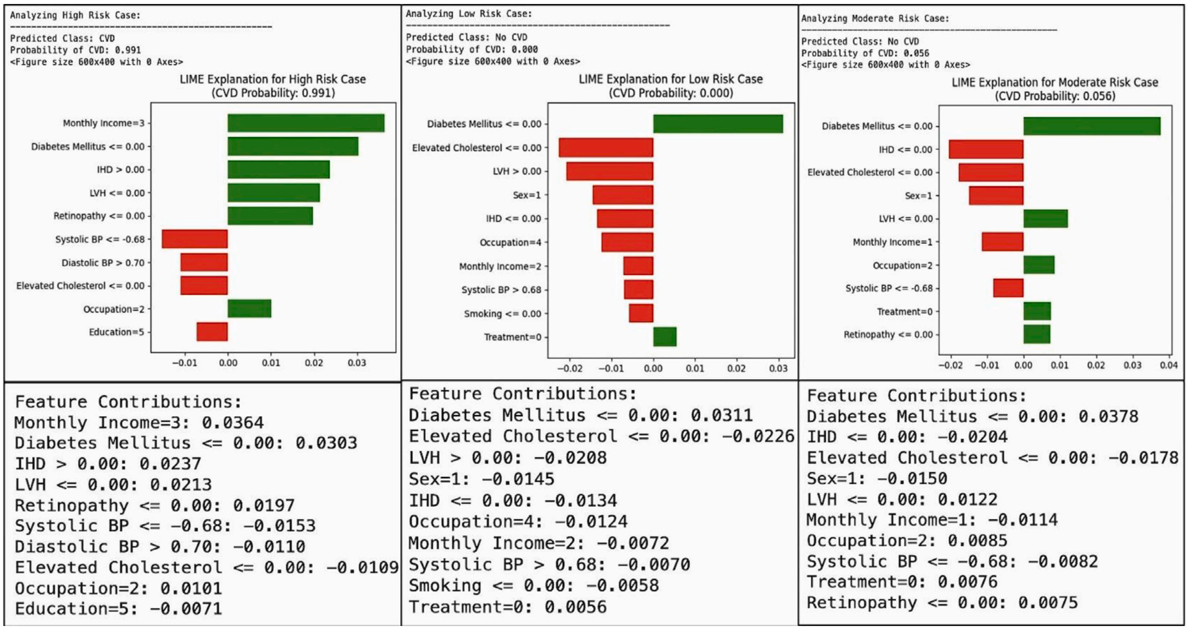


Fig. 9. Interpretable machine learning: LIME-based analysis for cardiovascular disease prediction.

factors. This study provides actionable insights to improve cardiovascular health outcomes in vulnerable populations by addressing disparities and integrating comorbidity management into care models.

Interpretable Machine Learning: LIME-Based Analysis for Cardiovascular Disease Prediction in Fig. 9 .

The provided LIME analysis delves into the contribution of individual features to CVD predictions for high-risk, low-risk, and moderate-risk cases. These values offer actionable insights for 'Hypertension Control in Resource-Constrained Settings: Bridging Socioeconomic Gaps with Predictive Insights'. Below is an interpretation based on feature values and their implications.

High-Risk Case

- Predicted Class: CVD with a probability of 0.991.
- Key Positive Contributions:
- Monthly Income = 3: This contributes a significant positive weight of 0.0364 to the prediction, indicating that higher income may correspond to certain lifestyle factors or clinical conditions exacerbating the risk.
- Diabetes Mellitus (<= 0.00): Adds 0.0303, showing the importance of diabetes as a significant determinant of CVD risk in this case.
- IHD > 0.00 and LVH <= 0.00: Contribute 0.0237 and 0.0213, respectively, underscoring the compounding effect of ischemic heart disease and left ventricular hypertrophy on the overall cardiovascular burden.
- Retinopathy <= 0.00: Adds 0.0197, reflecting how microvascular complications further elevate risk.
- Key Negative Contributions:
- Systolic BP <= −0.68 and Diastolic BP > 0.70: These negatively impact the prediction by −0.0153 and −0.0110, respectively, suggesting that controlled BP could partially mitigate the risk.
- Elevated Cholesterol = 0.00: A contribution of −0.0109 indicates how the absence of hyperlipidemia can lower the predicted risk.

The high probability highlights the cumulative impact of multiple adverse factors, particularly chronic conditions like diabetes and IHD. This emphasises the need for targeted interventions addressing these comorbidities.

Low-Risk Case

- Predicted Class: No CVD with a probability of 0.000.
- Key Negative Contributions:
- Diabetes Mellitus (<= 0.00): A substantial negative weight of −0.0311 indicates that the absence of diabetes is crucial in reducing risk.
- Elevated Cholesterol = 0.00: Contributes −0.0226, showing the protective effect of normal cholesterol levels.
- LVH > 0.00 and Smoking <= 0.00: Add −0.0208 and −0.0058, respectively, reflecting how the absence of structural heart abnormalities and smoking reduces risk.
- Systolic BP > 0.68: A minimal contribution of −0.0070 indicates well-controlled BP.
- Key Positive Contributions:
- Treatment = 0.0056: This marginally increases the prediction probability, suggesting room for more comprehensive management.

In this case, the zero probability for CVD emphasises the protective role of controlled risk factors, particularly diabetes and cholesterol. This underscores the value of early detection and management strategies to prevent disease progression.

Moderate-Risk Case

- Predicted Class: No CVD with a probability of 0.056.
- Key Positive Contributions:
- Diabetes Mellitus (<= 0.00): Adds 0.0378, making it the most significant feature in this case, highlighting its role in elevating CVD risk even at moderate levels.
- Treatment = 0.0076: This adds a positive weight, showing partial efficacy in controlling risk.
- Key Negative Contributions:
- IHD <= 0.00 and Elevated Cholesterol = 0.00: Contribute −0.0204 and −0.0178, respectively, reducing the risk and indicating the importance of managing lipid profiles and ischemic conditions.
- Systolic BP <= −0.68: A contribution of −0.0082 highlights the role of adequate BP control.
- Occupation = 2 and Monthly Income = 1: Contribute −0.0085 and −0.0114, suggesting potential socioeconomic factors that may indirectly affect risk through access to healthcare and lifestyle choices.

This case demonstrates the need for aggressive management of modifiable risk factors like diabetes and cholesterol to prevent further escalation of CVD risk. The analysis provides scientific evidence for prioritising interventions in resource-constrained settings:

- 1. Targeted Risk Factor Management: • Diabetes Mellitus emerges as a consistently high-impact feature across all cases, warranting targeted screening and management programs in hypertensive populations. • The significance of Elevated Cholesterol and LVH highlights the importance of routine lipid monitoring and echocardiographic evaluations.
- 2. Preventive Socioeconomic Strategies:• Features like Monthly Income and Occupation play notable roles, indicating that socioeconomic disparities may exacerbate health inequalities. Community-based health programs could address these gaps.
- 3.BP Control: • Controlled systolic and diastolic BP demonstrate a mitigating effect, reinforcing the importance of expanding access to antihypertensive medications and adherence monitoring systems.
- 4. Customised Treatments: • The minimal yet positive treatment effect in moderate and low-risk cases suggests the need for personalised therapeutic strategies, particularly for high-risk individuals.

The analysis strengthens the foundation for designing scalable, equity-focused interventions to bridge the management gaps in hypertension and cardiovascular disease in underserved populations.

Our observation is further supported by a recent longitudinal study in Northern Bangladesh, which found a high prevalence of poor medication adherence that was directly linked to uncontrolled blood pressure [58].The high rate of uncontrolled hypertension management is improved with patient education and adherence support.

5.1. Study limitations

This study has several limitations that should be considered when interpreting the findings. First, the sample size was relatively small, with only 300 participants, which may limit the generalisability of the results to the broader population. Secondly, the study relied on self-reported data for specific sociodemographic and clinical characteristics, which could introduce recall bias or inaccuracies in the reported information. Thirdly, the study's cross-sectional design precludes any causal inferences about the relationships between hypertension control and associated risk factors. Longitudinal studies would be necessary to establish causality and better understand the temporal dynamics of hypertension control. Additionally, using a consecutive sampling technique and focusing on patients attending a single hypertension care centre may have introduced selection bias, as these patients might not represent the general hypertensive population. Finally, the study was conducted over a short period of three months, which may not capture seasonal variations or long-term trends in hypertension control and management. Despite these limitations, the findings provide valuable insights into hypertension control rates and associated factors in a resource-constrained setting. Addressing these limitations in future research could enhance the robustness and applicability of the results.

6. Future research

• Longitudinal Studies: Conducting future studies to validate findings over time and assess long-term outcomes. • Diverse Populations: Expanding research to include diverse and heterogeneous populations, enhancing the generalisability of results. • Advanced Predictive Analytics: Leveraging cutting-edge analytics to refine predictive models and enable real-time risk stratification for hypertension management. • Genetic and Biomarker Integration: Exploring the integration of genetic data and biomarkers to facilitate personalised hypertension treatment strategies. • Multimodal Interventions: Investigating comprehensive approaches that address broader determinants of hypertension control, including lifestyle, socioeconomic factors, and healthcare access. • Digital Health Solutions: Evaluating the impact of mobile health (mHealth) applications, telemedicine platforms, and wearable devices in improving treatment adherence and continuous monitoring. • Comorbidity Management: Developing targeted strategies for managing hypertension in the context of multimorbidities, such as diabetes, cardiovascular diseases, and hyperlipidemia.

7. Conclusion

Hypertension remains a critical public health challenge, particularly in resource-constrained settings where socioeconomic disparities, limited healthcare access, and systemic barriers exacerbate the disease burden. This study evaluated hypertension control rates and identified key sociodemographic, clinical, and lifestyle factors influencing hypertension management among 300 hypertensive patients in Rangpur, Bangladesh. The findings reveal that 28% of hypertensive patients achieved adequate BP control, with rural residents (42%, $p = 0.005$) and homemakers (37%, $p < 0.001$) demonstrating significantly higher control rates. These results highlight the importance of community-based interventions and targeted support for vulnerable populations. The study employed advanced machine learning models, including KNN, which achieved an exceptional predictive accuracy of 99%, outperforming other models such as Random Forest, Gradient Boosting, and Logistic Regression. SHAP and LIME analyses provided interpretable insights into key predictors, highlighting the critical role of education level (post-graduate OR = 1.17, $p < 0.001$), urban residence (OR = 1.12, $p < 0.001$), and comorbidities like diabetes (OR = 0.93, $p = 0.006$) and ischemic heart disease (OR = 0.95, $p = 0.004$). These findings emphasise the need for integrated care approaches that address medical and social health determinants. The study also revealed that 74.3% of patients were on combination antihypertensive therapy, yet control rates remained suboptimal, suggesting gaps in medication adherence, patient education, and lifestyle modifications. Key modifiable risk factors, such as elevated cholesterol (SHAP value = 0.097) and unhealthy dietary habits (SHAP value = 0.077), significantly contributed to poor hypertension control. These findings highlight the importance of lifestyle interventions, including dietary modifications and physical activity, in improving hypertension outcomes. The sensitivity analysis further validated the predictive model's robustness, with socioeconomic variables like occupation (sensitivity score = 0.1349) and education (sensitivity score = 0.1277) emerging as the most influential predictors. It underscores the need for targeted interventions addressing structural inequalities, such as disparities in access to education and stable employment, which are prevalent in resource-constrained settings. While this study's hypertension control rate of 42% aligns with findings from similar settings, the urgent need for targeted interventions remains. There is an urgent need for innovative and inclusive strategies to bridge the gap in hypertension management. Addressing socioeconomic disparities, optimising treatment regimens, and fostering patient engagement are critical steps towards reducing the burden of hypertension and its complications in resource-constrained environments. Future research should focus on longitudinal studies to assess the long-term impact of these interventions and explore the scalability of predictive analytics in diverse healthcare settings. By integrating predictive insights with actionable strategies, this study provides a roadmap for improving hypertension control and achieving equitable healthcare outcomes in underserved populations. The findings advocate for scalable, data-driven interventions that address systemic and individual-level barriers, ultimately contributing to the global effort to reduce the burden of cardiovascular disease.

CRediT authorship contribution statement

Md Abul Kalam Azad: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Md Abu Sufian:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Lujain Alsadder:** Writing – review & editing, Validation, Formal analysis. **Sadia Zaman:** Writing – review & editing, Visualization, Validation, Formal analysis. **Wahiba Hamzi:** Writing – review & editing, Validation, Formal analysis. **Amira Ali:** Writing – review & editing, Validation, Formal analysis. **Md. Zakir Hossain:** Writing – review & editing, Validation, Resources, Formal analysis, Data curation. **Boumediene Hamzi:** Supervision, Project administration,Validation, Funding acquisition.

Ethics statement

The study complied with the ethical guidelines set forth by the Institutional Review Board (IRB) of the Hypertension and Research Centre, Rangpur, Bangladesh. The data used in this study were collected retrospectively from the centre's records and registration database, and no direct interaction with participants was involved. All data were anonymised before analysis to ensure confidentiality and privacy. The study was conducted under the ethical standards applicable to research in Bangladesh, as approved by the IRB.

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Code availability

The code and scripts used for data analysis, machine learning modelling, and visualisation in this study are publicly available on GitHub. The repository includes detailed documentation to facilitate reproducibility and further research. The code can be accessed at the following link: GitHub Repository: https://github.com/datascintist-abusufian/Hypertension-Control-in-Resource-Constrained-Settings

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Data availability

The dataset supporting this study, titled *Simulated Dataset for Hypertension Management and Risk Analysis*, is publicly accessible on the Mendeley Data platform. This dataset includes 10,000 patient records designed for advanced research in hypertension management, predictive modelling, and risk factor analysis. The data has been structured to facilitate applications in clinical research, machine learning, and statistical analysis.

- **Access Link:** https://data.mendeley.com/datasets/wj65h5tnp4/1 https://data.mendeley.com/datasets/wj65h5tnp4/2
- **Repository:** Mendeley Data
- **File Format:** Microsoft Excel (.xlsx)
- **Features:** Contains 19 variables spanning demographic, clinical, and treatment-related data.
- **License:** Open access for non-commercial academic and research purposes.

Researchers are encouraged to use this dataset for studies in hypertension control, treatment optimisation, and complications prediction. Proper citation of the dataset and adherence to the repository's terms of use are requested.

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