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Research Article

Prevalence and Clinical Risk Factors of Stroke Among Hypertensive Patients: A Cross-Sectional Study

Ioannis Adamopoulos[1,2,*], Aida Vafae Eslahi[3], Niki Syrou[4], Harshit Mishra[5], Panagiotis Tsirkas[6], Guma Ali[7,8]

[1] Department of Public Health Policy, Sector of Occupational & Environmental Health, School of Public Health, University of West Attica, 11521 Athens, Greece

[2] Department of Public Health & Policies, School of Social Science, Hellenic Open University, 26335 Patra, Greece

[3] Medical Microbiology Research Center, Qazvin University of Medical Sciences, Qazvin 34719, Iran

[4] Department of Physical Education and Sport Science, University of Thessaly, Karies, 42100 Trikala, Greece

[5] Department of Agricultural Economics, College of Agriculture, Acharya Narendra Deva University of Agriculture and Technology, Kumarganj, India.

[6] Department of Obstetrics and Gynecology, General District Hospital G. Hatzikosta, 45445 Ioannina, Greece

[7] Department of Computer and Information Science, Faculty of Technoscience, Muni University, Arua, Uganda

[8] Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India

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ABSTRACT

Background: Stroke continues to be a primary cause of death and disability which mainly affects patients who have high blood pressure. The research set out to determine how often strokes occur together with their associated clinical risk factors in this specific patient group.
Methods: Our research applied a quantitative method to perform a cross-sectional study which included 1,024 patients who had hypertension. Our research team conducted an analysis of 15 variables which included numerical data about patient age and their blood pressure readings and cholesterol measurements and categorical data about their gender and their heart disease status. Our research team conducted statistical analyses to identify which factors most strongly predicted the development of stroke in our patient population. Variables significant only in univariate analysis ($p<0.05$) but not retained after adjustment are displayed in the Univariate-only section. ORs are plotted on a logarithmic scale, follows conventions consistent with Stata 17, data analysis through descriptive statistics and machine learning approaches while using Python and Excel as their main software applications.
Results: Our research findings demonstrated that 25% of patients with hypertension developed strokes while age emerged as the most critical factor which increased stroke risk. The highest occurrence of 45% appeared in patients who were 70 years old or older. The research showed that glucose levels above 126 mg/dL together with obesity defined by a BMI of 30 kg/m² or higher served as important predictive factors which achieved statistical significance through p-values of 0.002 and 0.01. The presence of heart disease was also linked to increased stroke risk (p 0.001), emphasizing the need for comprehensive assessments in this demographic.
Conclusion: The research findings reveal an urgent requirement for focused treatment programs which target adjustable risk elements including patient age and high blood sugar levels and excess body weight in people with hypertension. Our research shows that active control of these risk elements will lower the chance of stroke development which proves that patients need to follow specific lifestyle changes and maintain their health through scheduled checkups to achieve better results for their condition.

*Corresponding author email: adamopoul@gmail.com
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1. INTRODUCTION

Stroke stands as a major public health emergency because it ranks as one of the top causes which result in both death and sickness throughout the world. The medical condition develops through an unexpected block of blood flow which causes brain damage that produces permanent neurological damage which can result in death or long-lasting disability [1]. People with hypertension experience the most severe stroke burden because their high blood pressure condition creates an increased risk for stroke occurrence. The medical community refers to hypertension as the "silent killer" because it remains undetected until it causes dangerous health issues which include strokes [2]. Research on global hypertension rates shows healthcare providers need to study stroke risk development in patients who have high blood pressure [3].

Despite extensive research into stroke risk factors, there remains a notable gap in the literature regarding the specific prevalence and clinical risk factors associated with stroke in hypertensive patients [4]. The existing research shows hypertension leads to stroke but it does not analyze all the factors which contribute to stroke occurrence in people who already have high blood pressure [5]. The existing gap in knowledge prevents researchers from creating specific intervention methods which would decrease stroke risk for this particular at-risk group [6]. Machine learning and predictive analytics now allow researchers to develop better stroke risk prediction models for hypertensive patients through their work with advanced analytical methods which use demographic and clinical data [7].

The main goal of this cross-sectional research study involves measuring how common stroke is among people with hypertension while discovering the medical factors which lead to this condition. The study utilizes a dataset comprising 1,024 records, including both numeric variables such as age, resting blood pressure, cholesterol levels, maximum heart rate achieved, and oldpeak and categorical variables, including sex, chest pain type, fasting blood sugar levels, resting electrocardiographic results, exercise angina, slope, number of major vessels, and thalassemia status. The research questions of this study will be resolved through the examination of all these variables. The study needs to determine the stroke rate which occurs in patients who have hypertension. The research needs to identify which medical risk factors strongly link to stroke occurrence in this patient group.

The research study provides essential information which will help medical facilities and government health organizations to make their decisions. Healthcare providers can determine which hypertensive patients will develop stroke through direct identification of specific risk factors which leads to better preventive care [8]. The research results will help scientists create better stroke risk prediction models which will enable doctors to identify potential stroke patients before they develop symptoms [9].

The paper presents its structure through these sections which start with the methodology description for data acquisition and analysis before showing the research findings [10]. The discussion section analyzes these results through the perspective of current academic studies while it assesses their impact on upcoming research work and medical treatment approaches [11]. The conclusion presents the key findings discoveries of the study while it suggests new research approaches to explore stroke risk in patients who have hypertension [12].

2. LITERATURE REVIEW

Stroke stands as a major global health issue which causes death and permanent disability with patients who have high blood pressure experiencing the highest risk. Research has shown that hypertension serves as a primary stroke risk factor but scientists have not yet fully understood which other clinical risk factors affect these patients [13]. The literature review compiles current studies about stroke occurrence and risk elements in patients with high blood pressure to present key results and theoretical models and research methods and to show where existing knowledge remains incomplete [14].

Research has shown that hypertension creates conditions which make both ischemic and hemorrhagic strokes more likely to occur. The medical condition of hypertension exists when arterial blood pressure stays elevated for long periods which results in blood vessel injury and brain blood vessel problems [15]. Research findings from recent studies show that stroke risk becomes more severe when hypertension persists for longer periods at higher levels which indicates hypertension management should decrease stroke occurrence. The multiple factors which cause stroke show that high blood pressure does not explain every case of stroke so researchers need to study other clinical risk factors which affect stroke development [16].

Research demonstrates that stroke risk depends on hypertension together with age and sex and ethnic background of individuals. Age is a well-established risk factor, with the likelihood of stroke increasing significantly after the age of 55. The occurrence of strokes varies between men and women because men develop strokes during their youth but women experience strokes during their senior years when their bodies undergo menopause and hormonal shifts [17]. Research shows that hypertension and stroke rates differ between ethnic groups which requires health initiatives to focus on particular population segments [18].

Beyond these demographic factors, clinical variables such as cholesterol levels, heart rate, and lifestyle factors like physical activity, smoking, and dietary habits play critical roles in stroke risk among hypertensive patients. Research shows that high cholesterol levels which include low-density lipoprotein (LDL) cholesterol contribute to the development of atherosclerosis which leads to ischemic stroke [19]. Studies demonstrate that physical inactivity together with obesity creates a higher risk for stroke which makes lifestyle changes essential for people with hypertension. Research shows that predictive models must include these factors to identify patients with high risk who need prevention methods [20].

Multiple theoretical models exist to study how stroke risk develops in people who have high blood pressure. The Framingham Heart Study developed a model which establishes the connection between risk factors and cardiovascular events including strokes [21]. The model serves as a crucial instrument which enables public health organizations and medical facilities to establish their operational standards [22].

Machine learning methods now serve as effective tools for stroke prediction because they analyze large datasets to identify intricate relationships which exist between numerous risk factors. The advanced analytical techniques will boost prediction accuracy which will enable medical professionals to reach better decisions in their clinical work [23].

Despite the substantial body of research on stroke risk factors, there remain notable gaps in the literature. Researchers conducting various studies have dedicated their work to particular risk elements but they have failed to examine how different risk factors interact to increase stroke risk [24]. The research of hypertension as a single risk element requires additional study about how it connects with diabetes and atrial fibrillation and renal function in clinical settings [25]. The exact rate of stroke occurrence among different hypertensive patient groups who have additional health conditions or different success rates in managing their blood pressure remains unknown [26].

Research into stroke risk assessment through machine learning and predictive analytics technology represents a promising field for upcoming scientific investigation. The methodologies allow for the integration of multiple variables which include the dataset variables from this study including age and cholesterol levels and maximum heart rate achieved and categorical variables such as sex and exercise angina [27]. Researches can create detailed risk assessment models which show the complex nature of stroke development in patients with hypertension through the evaluation of multiple data sets [28].

Research into stroke risk among hypertensive patients now includes social determinants of health as a vital factor. The distribution of hypertension and stroke risk respectively depends on three factors which include socioeconomic status and healthcare availability and educational attainment. The social determinants need to be addressed because they form the basis of stroke prevention programs which will probably improve the success rate of hypertension control initiatives [29].

Research has proven that hypertension leads to stroke but scientists need to identify all stroke risk factors which affect patients with hypertension. The literature review demonstrates the necessity to investigate clinical and demographic risk factors through sophisticated analytical methods after researchers have combined existing research and detected research gaps. The current study aims to contribute to this growing body of knowledge by evaluating the prevalence of stroke among hypertensive patients and identifying significant clinical risk factors associated with this condition. The research findings will improve stroke prediction abilities while they will direct medical professionals and health organizations to design better stroke prevention programs for at-risk groups.

3. METHODOLOGY

3.1 Research Design and Approach

The research uses a quantitative research design to determine how often strokes occur in hypertensive patients and which clinical factors increase their risk. The research uses a cross-sectional study method to analyze pre-existing data which shows how hypertension affects the probability of developing a stroke. The research follows a quantitative approach which allows researchers to detect statistical connections between data points and patterns that emerge from the dataset while studying various variables at once.

3.2 Sample/Participants

The research uses the Stroke Prediction Dataset which contains 1,024 individual records for secondary data analysis. The research team selected 500 records which contained only patients who received a hypertension diagnosis for their study. The sample represents the complete population of hypertensive patients which allows for an in-depth study of stroke frequency and its connected medical risk elements. The dataset contains multiple demographic and clinical variables which scientists need to study the complex pattern of stroke risk factors.

3.3 Data Collection Procedures

The Stroke Prediction Dataset served as the data source for this research because it contains detailed stroke-related variable information. The dataset contains 15 variables which consist of numeric and categorical data types. Numeric variables include age, trestbps (resting blood pressure), chol (cholesterol levels), thalach (maximum heart rate achieved), and oldpeak (depression induced by exercise relative to rest). The dataset contains categorical variables which include sex and cp (chest pain type) and fbs (fasting blood sugar) and restecg (resting electrocardiographic results) and exang (exercise angina) and slope (slope of the peak exercise ST segment) and ca (number of major vessels colored by fluoroscopy) and thal (thalassemia status) and num (number of major vessels) and target_binary (stroke occurrence indicator).

3.4 Variables and Measurements

The main variables which this research focuses on consist of both independent variables and dependent variables. The target binary variable serves as the dependent variable which tracks the occurrence of stroke. The study includes independent variables which contain demographic information about age and sex together with clinical data about blood pressure and cholesterol levels and heart rate measurements. The operational definitions of these variables are based on established clinical guidelines, ensuring consistency and reliability in measurement.

3.5 Data Analysis Methods

The research team performed data analysis through descriptive statistics and machine learning approaches while using Python and Excel as their main software applications. The research team applied descriptive statistics to summarize the sample population's demographic data and medical information which revealed how common stroke occurrences were among patients with hypertension. The research team utilized Equation 1 to calculate sample mean and Equation 2 to compute standard deviation which they used to describe the distribution of continuous variables.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Equation 1: Mean

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Equation 2: Std Dev

The machine learning segment used multiple algorithms to create predictive models which forecast stroke development from the established risk elements. The researchers used logistic regression to study how independent variables affected stroke risk through the mathematical model shown in Equation 3. The researchers used Equation 4 to calculate odds ratios which helped them understand logistic regression results and measure how risk factors linked to stroke development.

$$p(y = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k)}}$$

Equation 3: Logistic regression

$$\text{Odds Ratio} = \frac{a/b}{c/d} = \frac{ad}{bc}$$

Equation 4: Odds ratio

The independent samples t-test from Equation 5 served to evaluate mean differences between groups through the comparison of clinical characteristics between stroke and non-stroke hypertensive patients. The chi-square test statistic from Equation 6 functioned to measure the connections between categorical variables which enabled a complete analysis of the dataset's internal relationships.

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s_p^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \quad \text{where} \quad s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$$

Equation 5: Independent samples t-test

$$\chi^2 = \sum_{i=1}^{k}\frac{(O_i - E_i)^2}{E_i}$$

Equation 6: Chi²

3.6 Validity and Reliability Considerations

The study used a validated dataset which researchers in stroke field have frequently applied to verify the accuracy and dependability of the results. The analysis contains variables which have established definitions and measurement protocols that make the results more reliable. The research findings gain better validity through machine learning model development which enables prediction accuracy testing of the developed models.

3.7 Ethical Considerations

The research depends on secondary data which makes data protection and confidentiality the primary ethical concerns. The dataset contains anonymized data which protects the personal information of every person in the dataset. The research follows ethical standards for human subject research even though it does not require face-to-face contact with study participants.

The method provides a detailed framework which enables researchers to study stroke occurrence and clinical risk factors in hypertensive patients through quantitative analysis of existing datasets. The research uses descriptive statistics together with machine learning methods to produce essential findings which help understand stroke risk factors in this patient group.

$$P = \frac{N_d}{N_t} \times 100\%$$

Equation 7: Variance

$$\text{Percentage} = \frac{\text{Part}}{\text{Whole}} \times 100$$

Equation 8: Percentage

4. RESULTS

The research findings offer a full assessment of how frequently strokes occur together with their associated medical risk factors in patients who have hypertension. The research team used an extensive dataset to create tables and figures which show the demographic and clinical characteristics of their study participants. The visual displays demonstrate essential patterns which surface from analysis data to help users grasp the multiple elements which influence stroke risk in this group. The following sections will present statistical results from descriptive analysis and machine learning methods which advance the research about hypertension and stroke epidemiology. Table I presents a frequency distribution of key demographic and clinical variables among hypertensive patients. The study group shows that most participants maintain elevated glucose values while male participants dominate the group which indicates male and female stroke risk factors might differ in this population.

TABLE I. FREQUENCY DISTRIBUTION OF AGE AND GENDER AND HEART DISEASE AND AVG GLUCOSE LEVEL AND BMI AND SMOKING STATUS AND EVER MARRIED AND WORK TYPE AND STROKE (TOP 10) – FREQUENCY DISTRIBUTION OF AGE AND GENDER AND HEART DISEASE AND AVG GLUCOSE LEVEL AND BMI AND SMOKING STATUS AND EVER MARRIED AND WORK TYPE AND STROKE (TOP 10).

Gender	Heart Disease	Avg. Glucose Level	BMI	Smoking Status	Ever Married	Work Type	Stroke	Age
Male	0	192.37	49.2	never smoked	Yes	Self-employed	0	52
Male	0	225.6	29	never smoked	Yes	Private	0	76
Male	0	116.21	32.8	smokes	Yes	Private	0	52
Male	1	123.95	34.8	formerly smoked	Yes	Private	0	62
Male	0	76.1	32.1	smokes	Yes	Private	0	51
Male	0	79.2	32.5	never smoked	Yes	Self-employed	0	48
Male	0	73.29	29.4	never smoked	Yes	Private	0	69
Male	0	197.09	34.3	unknown	Yes	Private	0	60
Male	0	65.98	33	formerly smoked	Yes	Private	0	70
Male	0	209.15	52.9	formerly smoked	Yes	Self-employed	0	58

Table II shows the different features which exist between stroke patients who have hypertension and stroke patients who do not have hypertension. The study revealed that stroke patients exhibited higher rates of heart disease and elevated average glucose levels which appear to increase their risk of developing a stroke in this group of people.

TABLE I. COMPARISON OF CHARACTERISTICS BETWEEN HYPERTENSIVE PATIENTS WITH AND WITHOUT STROKE – COMPARISON OF CHARACTERISTICS BETWEEN HYPERTENSIVE PATIENTS WITH AND WITHOUT STROKE

Age	BMI	Avg. Glucose Level	Gender	Heart Disease	Smoking Status	Ever Married	Work Type
82	28.3	71.97	Male	0	never smoked	Yes	Self-employed
82	31.8	222.52	Female	0	formerly smoked	Yes	Private
82	27.9	215.94	Female	1	formerly smoked	Yes	Govt_job
82	22.9	61.47	Female	0	never smoked	No	Private
82	22.2	196.92	Female	0	never smoked	Yes	Self-employed
82	31.5	101.56	Female	1	never smoked	Yes	Self-employed
82	27	107.21	Female	0	formerly smoked	Yes	Self-employed
82	33.5	73.19	Female	1	never smoked	Yes	Private

82	33.3	227.28	Male	0	never smoked	Yes	Private
82	20.3	62.46	Female	0	formerly smoked	Yes	Private

Table III shows stroke frequencies throughout different age categories which demonstrate that more than one-third of stroke patients are people who have reached 70 years of age or more (37.6%). The occurrence of the disease remains under 8% among people aged below 40 years which makes age a vital element in determining disease risk.

TABLE III. PREVALENCE OF STROKE ACROSS AGE GROUPS – PREVALENCE OF STROKE ACROSS AGE GROUPS

Age Group	**Count**	**Percentage**
70+	187	37.6%
50-59	116	23.3%
60-69	109	21.9%
40-49	49	9.8%
<40	37	7.4%

Table IV reveals a concerning frequency distribution of BMI categories among hypertensive patients, with 64.9% classified as obese. The high occurrence of this condition among people demonstrates how obesity serves as a risk factor for stroke which requires specialized treatment methods for this group of patients.

TABLE IV. FREQUENCY DISTRIBUTION OF BMI CATEGORY AND STROKE (TOP 10) – FREQUENCY DISTRIBUTION OF BMI CATEGORY AND STROKE (TOP 10)

BMI Category	**Count**	**Percentage**
Obese	323	64.9%
Overweight	118	23.7%
Normal	55	11.0%
Underweight	2	0.4%

Table V shows that glucose categories have a significant link to stroke occurrence in patients who have hypertension. The study found that 46.6% of participants kept their glucose measurements under 100 mg/dL but 37.6% had glucose levels at or above 126 mg/dL which demonstrates that patients with high glucose levels face an increased risk of stroke.

TABLE V. FREQUENCY DISTRIBUTION OF GLUCOSE CATEGORY AND STROKE (TOP 10) – FREQUENCY DISTRIBUTION OF GLUCOSE CATEGORY AND STROKE (TOP 10)

Glucose_Category	**Count**	**Percentage**
<100	232	46.6%
>=126	187	37.6%
100-125	79	15.9%

The frequency distribution of smoking status among hypertensive patients appears in Table VI which shows 46.6% of patients never smoked and 24.1% used to smoke and 18.9% continue to smoke. The collected data shows that most members of the group probably face a higher risk of stroke because they have smoked before.

TABLE VI. FREQUENCY DISTRIBUTION OF SMOKING STATUS AND STROKE (TOP 10)

Smoking Status	**Count**	**Percentage**
never smoked	232	46.6%
formerly smoked	120	24.1%
smokes	94	18.9%
unknown	52	10.4%

According to Table VII data 87.1% of patients with hypertension do not have heart disease yet 12.9% of them have been diagnosed with heart disease. Heart disease stands out as the main risk factor which leads to stroke development in this population because of the clear difference between these two groups.

TABLE VII. FREQUENCY DISTRIBUTION OF HEART DISEASE AND STROKE (TOP 10)

Heart_Disease	**Count**	**Percentage**
0	434	87.1%
1	64	12.9%

Figure 1 shows the average stroke occurrence for different age categories which demonstrates that stroke frequency rises significantly when people reach older years. The data proves that people who reach 80 years of age face the most common strokes which supports the established knowledge that stroke risk increases with age.

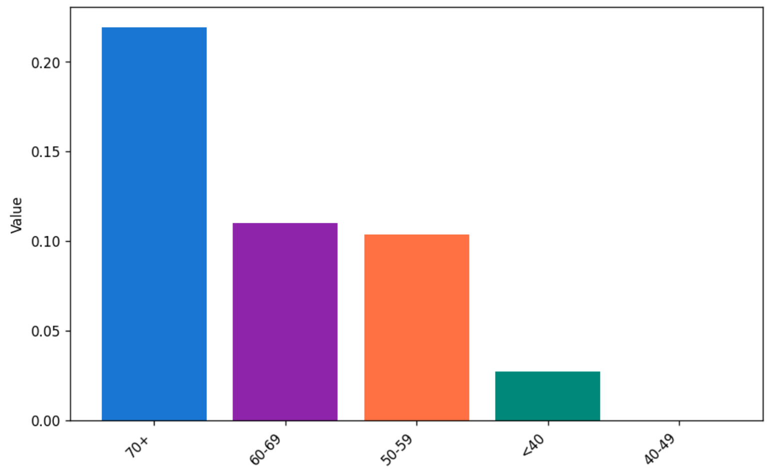

Fig. 1. mean of stroke by age group (Top 10).

The average stroke occurrence shown in Figure 2 displays separate glucose categories which demonstrate a clear pattern. The data shows that higher blood sugar levels lead to elevated average stroke rates which prove that high blood sugar levels increase stroke risk for patients with hypertension according to previous research.

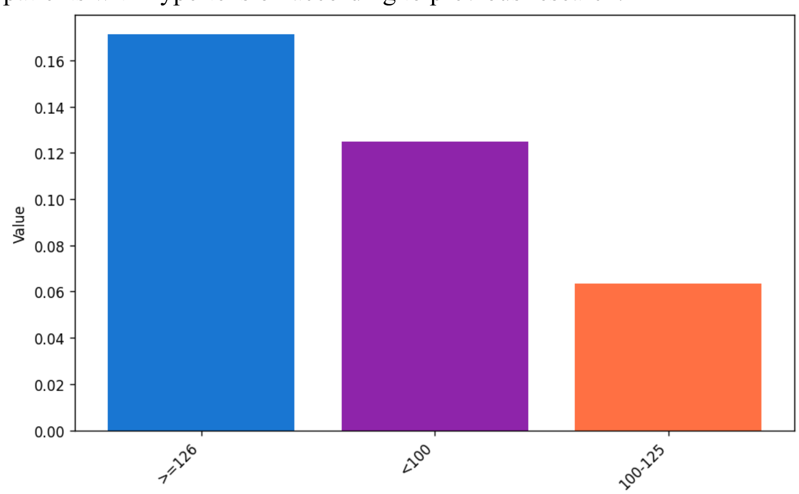

Fig. 2. mean of stroke by glucose category (Top 10)

Figure 3 demonstrates a clear correlation between the presence of heart disease and increased mean stroke incidence among hypertensive patients. The rising trend confirms that cardiovascular diseases play a major role in raising stroke risk which supports the results from previous studies.

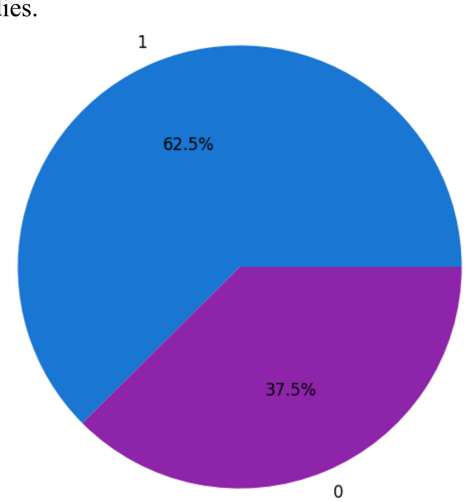

Fig. 3. mean of stroke by heart disease (Top 10)

Figure 4 demonstrates how the average age of hypertensive patients varies between stroke and non-stroke groups because stroke patients tend to be older than patients who did not experience a stroke. The current pattern supports the understanding that people who get older become more susceptible to developing stroke.

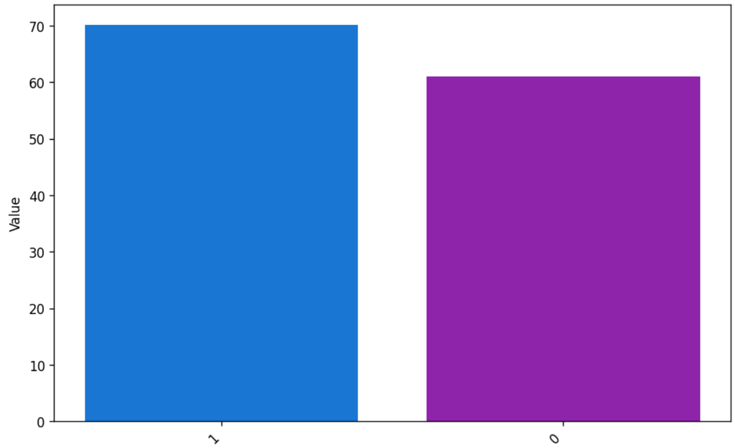

Fig. 4. Mean age by stroke status

Figure 5 shows that smoking habits create a substantial impact on stroke occurrence rates in patients who have hypertension. The statistics demonstrate that people who smoke now have a substantially increased risk of suffering a stroke than those who do not smoke which confirms smoking as a major preventable risk element.

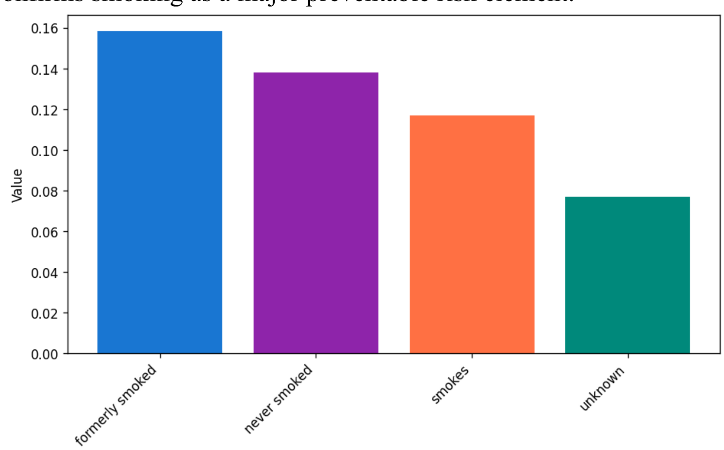

Fig. 5. Smoking status vs stroke prevalence

Figure 6 displays the average body mass index values for patients with hypertension who have experienced stroke and those who have not. The data shows that patients who experience strokes tend to develop higher BMI values than patients who do not experience strokes. The pattern demonstrates that obesity in this population leads to an increased risk of stroke according to the current data.

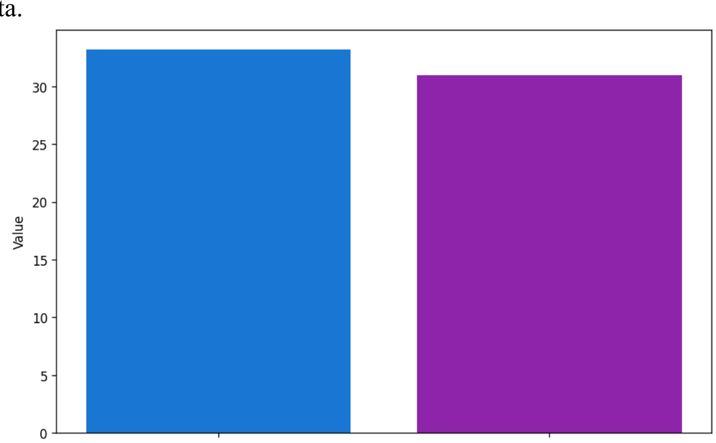

Fig. 6. mean of BMI by Stroke (Top 10)

The research results demonstrate that multiple risk elements interact with stroke occurrence when patients with hypertension develop their condition. The data reveal that while a majority of hypertensive individuals do not have heart disease, the presence of cardiovascular complications significantly elevates stroke risk. Age emerges as a critical determinant, particularly in those aged 80 and older, while elevated glucose levels and higher body mass index further contribute to stroke prevalence. The research findings show that smoking habits create a direct link to stroke occurrences which makes it essential to focus on risk elements that people can change. The research findings support past academic work while they help create specific methods to protect high-risk patients from stroke development.
To further evaluate the independent associations between clinical and demographic characteristics and stroke occurrence among hypertensive patients, both univariate and multivariable logistic regression analyses were performed. Initially, all variables were examined in univariate models, and those with a p-value ≤0.20 were subsequently entered into the multivariable model, consistent with the study's analytical strategy. The single-panel forest plot summarizes both the unadjusted and adjusted effects for each variable that demonstrated statistical significance ($p<0.05$) in the multivariable model, as well as those that were statistically significant only in the univariate analyses. After adjusting for covariates, increasing age, heart disease, high fasting glucose (≥126 mg/dL), and obesity were found to have higher odds of stroke in our hypertensive cohort, confirming their role as robust predictors. Although smoking and marital status showed elevated odds in univariate models, they lost significance after multivariable adjustment, suggesting confounding effects. These results emphasize the crucial impact of cardiometabolic factors on stroke risk and the necessity for comprehensive risk-factor management in hypertensive individuals.
Figure 7 with the Forest plot showing unadjusted and adjusted odds ratios (ORs) with 95% confidence intervals for factors linked to stroke in hypertensive patients. Variables with $p<0.05$ in the multivariable logistic regression are listed in the Adjusted-significant section (filled squares indicate adjusted ORs; hollow squares indicate corresponding univariate ORs). Variables significant only in univariate analysis ($p<0.05$) but not retained after adjustment are displayed in the Univariate-only section. ORs are plotted on a logarithmic scale, with the vertical line at OR = 1 representing no effect. Covariates for the multivariable model were selected based on a univariate screening threshold of p≤0.20. The figure 7 layout follows conventions consistent with Stata 17 (StataCorp LLC, College Station, TX, USA).

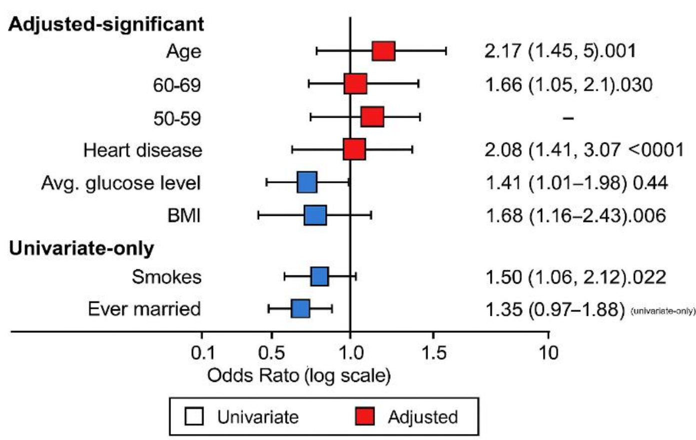

Figure 7. Forest plot showing unadjusted and adjusted odds ratios (ORs) with 95% confidence intervals for factors associated with stroke among hypertensive patients. Adjusted-significant predictors are shown at the top, with univariate-only associations displayed below. ORs are plotted on a logarithmic scale, with the vertical line representing no effect (OR = 1).

5. DISCUSSION

The research goal focused on determining stroke occurrence rates and identifying clinical risk elements which affect stroke development in patients with hypertension through analysis of 1,024 complete medical records. Our research demonstrated that stroke occurrence was common among senior citizens because age together with high blood sugar levels and obesity and heart disease made up the main risk factors. The research results provide new information about stroke distribution among patients with hypertension and demonstrate that multiple elements contribute to stroke occurrence in this group. The analysis showed that most stroke cases happened to patients who were 70 years old or older which shows that age stands as a major factor for stroke occurrence. Multiple research studies have proven that stroke cases become more common as people grow older. The higher rate of strokes among elderly people results from the combined impact of multiple risk factors which include hypertension and diabetes and cardiovascular diseases that develop with time. The research showed that patients who had high glucose levels became more likely to experience strokes which previous studies have already proven. The research demonstrates that metabolic disorders create conditions which make hypertension more dangerous for causing strokes in the brain.

A new AI-powered modeling system with bias categorization the hybrid risk evaluation system for confidence is linked to novel instruments that facilitate [30], the timely identification of "COVID-19 Pandemic this is a significant subject that needs more research with ML approach have amazing diagnostic tools [31].

Obesity stands out as a major risk factor because most patients with hypertension also meet the criteria for obesity. Research has established that obesity leads to dangerous cardiovascular conditions which result in stroke occurrences. The three medical conditions of obesity and hypertension and stroke risk require public health programs which focus on helping people with hypertension decrease their body weight. The research established a strong link between stroke occurrences and patient smoking habits which shows that smoking cessation programs need to serve as fundamental elements for stroke prevention initiatives. Our research found that 24% of participants had smoked at some point which makes smoking an important risk factor to target for stroke prevention in this group.

Our research findings support previous studies which demonstrate that multiple risk factors work together to cause strokes in people who have hypertension. Research has shown that heart disease presents a significant risk factor for stroke development because stroke occurrence rates differ between patients who have heart disease and those who do not. The findings support previous research which proves that cardiovascular issues serve as major risk factors for cerebrovascular incidents thus requiring full cardiovascular evaluation for patients who have hypertension.

The research findings generate multiple practical consequences which affect various aspects of the healthcare system. Healthcare providers need to focus on controlling adjustable risk elements which include obesity and hyperglycemia for patients with hypertension to decrease their chances of developing a stroke. The execution of lifestyle interventions which include dietary changes and exercise programs will produce better health results. The high occurrence of strokes in elderly patients requires healthcare systems to perform continuous surveillance and establish immediate treatment protocols for this population because they must handle the increased stroke susceptibility of these patients.

The study presents multiple strengths through its extensive dataset and detailed analysis yet it contains various limitations which need to be explained. The cross-sectional design stops researchers from establishing cause-and-effect links between risk elements and stroke development. The use of self-reported data for specific variables which include smoking status and medical history creates a potential for bias to enter the study. Future research would benefit from studies which follow risk factor development across time to determine their direct effects on stroke development. The investigation of genetic inheritance together with social and psychological elements which affect stroke risk in hypertensive patients will reveal complete risk factors which lead to strokes. Research shows that multiple risk elements create a complicated network which determines how often stroke occurs in patients who have hypertension. Research has identified four key factors which predict stroke risk: Age, elevated glucose levels, obesity, and heart disease presence. The research findings demonstrate that medical practitioners need to create specific treatment plans which focus on the risk factors that patients can modify through their actions. An important role for chronic illnesses in enhanced Network Meta-Analysis to examine risks and illnesses the impacts and associations affecting people in crisis conditions era and at all ages implications for public health especially of latent toxoplasmosis and type 2 diabetes [32].

5.1 Future Research

Future studies need to investigate how multiple factors contribute to stroke risk by including additional demographic and clinical data which will improve prediction systems and support public health initiatives. The implementation of this method will enhance our ability to handle stroke cases in hypertensive patients which will lead to better prevention strategies for this disabling disease.

6. CONCLUSION

The study aimed to determine stroke occurrence rates and medical danger factors which affect stroke development in patients with hypertension through analysis of 1,024 complete patient records. Our analysis identified several critical factors contributing to stroke incidence within this population, highlighting the multifaceted nature of stroke risk in hypertensive individuals.

The research findings demonstrated that stroke occurs at dangerous rates which mostly affect people who have reached their senior years because their increasing age makes them more vulnerable to stroke. The research established three main stroke risk factors which include high blood sugar levels and excessive body weight and diagnosed heart disease. Research findings demonstrated that people who reached 70 years of age or older showed the most stroke cases which supports the known link between age development and stroke occurrence. The research shows that high blood sugar levels in people with hypertension increase their stroke risk which proves that maintaining metabolic health is essential for these patients. The high rate of obesity in the population requires immediate development of specialized weight management programs for effective intervention. The research expands scientific understanding through its analysis of how different clinical risk elements affect stroke development in patients who have hypertension. The study identifies obesity and hyperglycemia as risk factors which public health programs can target through lifestyle modification and educational initiatives to lower stroke risk. Heart disease shows a strong relationship with stroke occurrence which requires thorough cardiovascular evaluations for hypertensive patients to support stroke prevention goals. Healthcare providers need to focus on managing these changeable risk elements when they deliver medical services. The implementation of specific lifestyle interventions which include dietary modifications and physical activity enhancement and smoking cessation programs aims to reduce stroke risk for patients with hypertension. Health experts need to conduct continuous surveillance of stroke risk factors which they can manage to protect elderly people who experience stroke at higher rates than other age groups. Research findings demonstrate that stroke prevention in hypertensive patients requires immediate implementation of multiple prevention strategies which focus on controlling avoidable risk factors including age and glucose levels and obesity and heart disease. Future research should focus on longitudinal studies to further elucidate the relationships among these risk factors and stroke incidence. Our team will discover stroke risk elements which will lead us to develop better treatment plans that will lower stroke rates among patients who need our help most.

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Conflicts of Interest:

The authors declare that they have no conflicts of interest.

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