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A Comparative Study of Univariate and Bivariate Logistic Regression on Hypertension and Obesity

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Abstract

Hypertension and obesity are non-communicable diseases (NCDs) whose joint burden is increasingly framed within Indonesia's disaster management policy as a form of non-natural disaster. These two conditions share common pathophysiological mechanisms, yet most studies model them independently, ignoring their inherent dependency. This study compares univariate and bivariate binary logistic regression models to jointly analyze hypertension and obesity using data from 12,592 Indonesian Family Life Survey (IFLS5) respondents, with age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate as predictors. The bivariate model revealed a significant positive dependence ($\theta = 1.258$, $p < 0.001$), confirming the need to explicitly model their joint association. Waist circumference emerged as the dominant physiological predictor for obesity, while advancing age was the strongest determinant of hypertension. The study also formalizes a criterion-based functional-form validation protocol combining the Box–Tidwell test, spline modeling, AIC/BIC, a likelihood-ratio test, and predictive-stability diagnostics into a reproducible decision rule. Model comparison based on AIC and BIC consistently favored the bivariate approach, although 10-fold cross-validation showed no significant difference in out-of-sample discriminative performance. These findings support Indonesia's efforts toward Sustainable Development Goal target 3.4 on reducing premature mortality from non-communicable diseases, though results reflect structural associations rather than causal superiority.

Keywords: Bivariate logistic regression; hypertension; IFLS5; non-communicable disease; obesity.

1. Introduction

Hypertension remains a major global health challenge and a leading contributor to cardiovascular mortality, with its prevalence continuing to rise in developing nations [1]. Among its key determinants, central obesity is consistently associated with metabolic disturbances and elevated vascular pressure, making the coexistence of both conditions a critical public health concern [1]. As non-communicable diseases (NCDs), the escalating and sustained burden of hypertension and obesity has increasingly been framed within Indonesia's disaster management discourse under the category of non-natural disaster (*bencana non-alam*), which Law No. 24/2007 on Disaster Management defines as encompassing large-scale epidemics and disease outbreaks [2]; controlling this burden is also central to the Sustainable Development Goal (SDG) target 3.4 of reducing

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premature mortality from NCDs by one-third by 2030 [3]. Moreover, hypertension and obesity share several anthropometric and physiological risk indicators, including waist circumference, handgrip strength, lung capacity, and pulse rate, suggesting common underlying mechanisms that may influence both conditions simultaneously [1, 4]. Nevertheless, most epidemiological studies continue to analyze hypertension and obesity separately, despite their frequent co-occurrence and inherent statistical dependence.

From a methodological perspective, modeling correlated binary outcomes using separate univariate logistic regression ignores their dependency structure, potentially leading to inefficient estimation and reduced statistical power [5]. Bivariate binary logistic regression addresses this limitation by jointly modeling both outcomes while explicitly estimating their residual association through the dependence parameter (θ), thereby providing a more comprehensive framework for investigating shared determinants of correlated diseases [5, 6]. Despite the well-established relationship between hypertension and obesity, applications of bivariate binary logistic regression to these conditions remain limited, particularly in the Indonesian population. Most local studies continue to rely on separate univariate analyses, leaving both the shared determinants and the dependence structure between the two conditions largely unexplored [7, 8]. Furthermore, previous applications of bivariate binary logistic regression have primarily focused on different disease combinations and populations, while several important methodological issues have received limited attention.

Accordingly, this study contributes to the existing literature in four respects. First, unlike previous studies that generally assume data are Missing Completely at Random (MCAR), this study empirically evaluates the missingness mechanism and demonstrates that the observed missing data more closely follow a Missing at Random (MAR) pattern driven by the survey design, a distinction with direct implications for the validity of complete-case estimation. Second, this study explicitly addresses the potential construct circularity between obesity, defined using Body Mass Index (BMI), and waist circumference as a predictor, a methodological concern that has rarely been discussed in previous applications of bivariate binary logistic regression.

Third, beyond evaluating relative model fit using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), this study assesses classification accuracy and the Area Under the Receiver Operating Characteristic Curve (AUC–ROC). Fourth, this study establishes a criterion-based protocol (Section 2.10) for reconciling detected nonlinearity with the need for interpretable odds ratios in bivariate binary logistic regression, integrating Box–Tidwell, spline modeling, relative fit indices, likelihood-ratio testing, and predictive-stability diagnostics into a reproducible decision rule. Therefore, this study aims to jointly model hypertension and obesity using individual-level data from the Indonesian Family Life Survey wave 5 (IFLS5). By incorporating shared anthropometric and physiological predictors within a unified bivariate binary logistic regression framework, this study evaluates whether explicitly accounting for the dependence between the two outcomes improves model fit and predictive performance compared with separate univariate logistic regression models, while providing a more comprehensive understanding of their shared epidemiological determinants and supporting national efforts toward disaster-risk mitigation and SDG target 3.4 monitoring. The remainder of this paper is organized as follows: Section 2 details the methodology and data construction, Section 3 presents the comparative analysis and discussion, and Section 4 concludes the paper.

2. Methods

This section describes the methodological framework used to compare the univariate and bivariate logistic regression approaches. It covers the data source and sample construction, variable definitions, model specification, diagnostic procedures, model comparison, cross-validation, and functional-form validation. The data source and construction of the analytical sample are described first.

2.1. Data Source and Sample Construction

This study used individual-level data from the Indonesian Family Life Survey wave 5 (IFLS5), combining the demographic cover module (`B3A_COV`) and physical health module (`BUS_US`) using the unique individual identifier (*pidlink*) [9]. The merged dataset initially contained **48,139** individuals.

Body Mass Index (BMI) was calculated from measured height and weight. Records with missing anthropometric data or biologically implausible BMI values (outside the range of 10–60 kg/m^2) were excluded ($n = 383$, 0.8%), leaving 47,756 records. A second quality-control step removed biologically implausible measurements, including zero handgrip strength ($n = 5$), zero lung capacity ($n = 8$), waist circumference below 50 cm ($n = 22$), pulse rate outside 40–150 bpm ($n = 18$). This excluded a further 53 records, yielding 47,703 observations before complete-case selection.

Table 1 summarizes the missing-data pattern for each variable, assessed independently rather than sequentially. Waist circumference showed the highest missingness (72.5%), followed by handgrip strength, pulse rate, age, and sex (approximately 32% each), while lung capacity had 20.6% missing values. Notably, 9,468 respondents (19.8%) were missing all six physical examination variables, indicating non-participation in the Book US examination module rather than isolated item non-response.

Table 1: Missing-data pattern by variable (independent, $n = 47,703$)

Variable	Non-Missing (n)	Missing (n)	% Missing
Waist circumference	13,108	34,595	72.5%
Blood pressure / Hypertension	32,199	15,504	32.5%
Handgrip strength	32,244	15,459	32.4%
Pulse rate	32,304	15,399	32.3%
Age	32,516	15,187	31.8%
Sex	32,517	15,186	31.8%
Lung capacity	37,878	9,825	20.6%
Complete-case sample	12,592	26.4% of 47,703	

Complete-case analysis across all model variables (age, sex, waist circumference, handgrip strength, lung capacity, pulse rate, and blood pressure) produced a final sample of 12,592 individuals, including 5,217 (41.4%) hypertensive and 4,633 (36.8%) obese participants, satisfying the recommended Events Per Variable (EPV) criterion [10].

Empirical assessment of the missingness mechanism

To evaluate the missingness mechanism, we examined whether missingness was associated with fully observed covariates [11]. Waist circumference missingness was strongly associated with age (point-biserial $r = -0.78$): measurements were entirely missing among respondents younger than 33 years, 50.2% missing among those aged 33–49, and nearly complete for those aged 50 years or older. This pattern reflects a survey-design restriction rather than random non-response, supporting a Missing at Random (MAR) mechanism. Consequently, the complete-case sample is effectively restricted to adults aged 33 years and above (mean age 53.4 years), compared with excluded respondents (mean age 28.5 years).

Handgrip strength and lung capacity also showed increased missingness among respondents aged 70 years and above (8.5% and 10.8%, respectively), suggesting that Missing Not at Random (MNAR) cannot be excluded because frailty may affect participants' ability to complete these measurements. This is acknowledged as a study limitation.

Blood pressure measurements showed a missingness rate (32.5%) closely comparable to handgrip strength, pulse rate, age, and sex (all approximately 32%), consistent with their shared origin in the Book US physical examination module and further supporting the survey-design-driven MAR mechanism described below.

Although complete-case analysis under MAR may introduce bias, inclusion of age in all regression models partially mitigates this concern. Given that missingness was driven primarily by survey design rather than health-related non-response, complete-case analysis was considered an appropriate, though imperfect, analytical approach. Its implications are discussed further in the conclusion section.

2.2. Diagnostic Criteria and Variable Definitions

To ensure methodological transparency and prevent construct circularity, the binary response variables were rigorously defined using standardized diagnostic criteria based on IFLS5 anthropometric and physiological measurements.

Hypertension: Blood pressure was measured multiple times during the survey fieldwork. The diagnostic criterion used in this study was based on the average of two valid systolic and diastolic blood pressure readings. A respondent was classified as hypertensive ($Y_1 = 1$) if the mean systolic blood pressure was $\geq$ 140 mmHg or the mean diastolic blood pressure was $\geq$ 90 mmHg. A respondent was classified as non-hypertensive ($Y_1 = 0$) only when the required blood pressure measurements were available and both the mean systolic and diastolic blood pressures were below these thresholds. Respondents for whom the required blood pressure measurements were missing or incomplete were coded as missing for the hypertension outcome and were not classified as non-hypertensive. These observations were subsequently excluded during complete-case selection.

Obesity: Obesity status was determined strictly using the Body Mass Index (BMI). BMI was calculated by dividing the respondent's weight in kilograms by the square of their height in meters (kg/m^2). A respondent was classified as obese ($Y_2 = 1$) if their calculated BMI was ≥ 25. Otherwise, they were classified as non-obese ($Y_2 = 0$).

It is crucial to emphasize that the definition of obesity in this study relies entirely on BMI (derived from standing height and total body weight). Consequently, the inclusion of waist circumference as an independent predictor variable does not introduce mathematical circularity. While BMI captures overall body mass, waist circumference serves as a distinct physiological proxy for abdominal (central) adiposity. Treating waist circumference as a separate predictor enables the model to evaluate the specific risk contribution of fat distribution independent of the baseline obesity classification. However, to address potential construct circularity between BMI-based obesity and waist circumference, a sensitivity analysis was additionally conducted by excluding waist circumference from the models to evaluate its impact on predictive performance.

Handgrip strength was measured in kilograms (kg), lung capacity in liters (L), and pulse rate in beats per minute (bpm); age was recorded in years, and waist circumference in centimeters (cm).The continuous predictor variables analyzed in the subsequent logistic regression models include age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate. For descriptive analysis purposes, several continuous variables were categorized into groups. Age was categorized into three groups: 33–45 years, 46–60 years, and more than 60 years, reflecting the sample's implicit age restriction described in Section 2.1. Waist circumference and handgrip strength were classified based on sex-specific cut-off points; high waist circumference was defined as $\geq$ 90 cm for males and $\geq$ 80 cm for females, while low handgrip strength was defined as $<$ 28 kg for males and $<$ 18 kg for females. Lung capacity was categorized using its median value as the cut-off point, and pulse rate was classified as "High" if it exceeded 100 beats per minute.

However, in the subsequent univariate and bivariate logistic regression models, these predictor variables were strictly analyzed in their original continuous scales. This methodological decision was made to maintain statistical power, capture the full underlying variability of the data, and prevent the loss of information that typically occurs when continuous variables are dichotomized or categorized.

With more than 4,600 observed positive cases for both hypertension and obesity within the final 12,592 complete cases, the sample overwhelmingly satisfies the Events Per Variable (EPV) threshold, which recommends at least 10 events per predictor to maintain model stability [10]. This ample sample size ensures that the Maximum Likelihood Estimation (MLE) algorithm converges smoothly and produces reliable parameter estimates.

2.3. Data Design

This study applies univariate and bivariate logistic regression approaches to model the relationship between hypertension and obesity. Initially, binary logistic regression models were fitted separately for each response variable to examine the individual effect of each predictor. Prior to joint modeling, the marginal Chi-square test (Section 2.7.2) was used to establish whether an unconditional statistical association exists between hypertension and obesity.

However, a marginal Chi-square test alone provides limited methodological justification for adopting a bivariate framework: it only indicates whether hypertension and obesity are unconditionally associated, without quantifying the strength of that association after adjusting for shared predictors, and without providing any measure of predictive utility. To address these limitations, a bivariate binary logistic regression model was subsequently employed, offering three specific advantages over the Chi-square test and separate univariate models:

1. **Conditional dependence estimation.** The bivariate model estimates the association parameter θ conditional on the covariates included in both marginal models, allowing a direct test of whether the dependence between hypertension and obesity persists after adjusting for age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate.
2. **Joint estimation efficiency.** By modeling both outcomes simultaneously rather than through two separate univariate models, the bivariate approach can, in principle, produce more efficient parameter estimates when the outcomes are correlated, reducing the specification bias that arises from ignoring their dependence structure.
3. **Predictive validation.** Unlike the Chi-square test, which only assesses statistical association, the fitted bivariate model permits direct evaluation of predictive performance. To ensure robust validation, avoid overfitting, and formally compare the predictive performance of the univariate and bivariate approaches, a 10-fold cross-validation procedure was employed, with folds generated via simple random partitioning of the complete-case sample. Within each fold, both the univariate and bivariate models were refitted on the same training partition and evaluated on the same held-out test partition, enabling a paired comparison of classification accuracy and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) across folds. Results are reported in Section 3, providing evidence of practical utility beyond statistical significance alone.

Model parameters for both the univariate and bivariate approaches were estimated using Maximum Likelihood Estimation (MLE), and statistical significance was evaluated using Wald tests. All analyses were performed in R: the `glm()` function was used to fit the univariate logistic regression models, while the `vglm()` function with the `binom2.or()` family from the `VGAM` package was used to fit the bivariate model.

2.4. Logistic Regression

Logistic regression models the relationship between a binary response variable and a set of predictor variables using the logit link function [12]. For the i-th individual, the model is expressed as shown in Eq. (1):

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} \tag{1}$$

where $p_i = P(Y_i = 1 \mid \mathbf{x}_i)$ is the probability of the event occurring, β_0 is the intercept, and β_j represents the coefficient of the j-th predictor.

The corresponding probability function is given in Eq. (2):

$$p_i = \frac{\exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ji}\right)}{1 + \exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ji}\right)} \tag{2}$$

In this study, two univariate logistic regression models were constructed for hypertension and obesity, using age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate as predictors. Both models were implemented in R using the `glm()` function with the binomial family and logit link.

2.5. Bivariate Binary Logistic Regression

Bivariate binary logistic regression is an extension of binary logistic regression used to simultaneously model two correlated binary response variables [5]. This model is appropriate when two binary outcomes may occur jointly and are assumed to have statistical dependence. In this study, the response variables are hypertension status and obesity status.

Let (Y_{1i}, Y_{2i}) denote the pair of binary response variables for the i-th individual, where:

$$Y_{1i}, Y_{2i} \in \{0, 1\}, \quad i = 1, 2, \ldots, n$$

with:

- $Y_{1i} = 1$ if the individual has hypertension and 0 otherwise,
- $Y_{2i} = 1$ if the individual is obese and 0 otherwise.

The marginal probabilities for each response variable are defined as:

$$p_{1i} = P(Y_{1i} = 1 \mid \mathbf{x}_i)$$

$$p_{2i} = P(Y_{2i} = 1 \mid \mathbf{x}_i)$$

where $\mathbf{x}_i$ is the vector of predictor variables.

The marginal logistic regression models are expressed as follows:

$$\log\left(\frac{p_{1i}}{1 - p_{1i}}\right) = \beta_{10} + \beta_{11}x_{1i} + \beta_{12}x_{2i} + \cdots + \beta_{1k}x_{ki}$$

$$\log\left(\frac{p_{2i}}{1 - p_{2i}}\right) = \beta_{20} + \beta_{21}x_{1i} + \beta_{22}x_{2i} + \cdots + \beta_{2k}x_{ki}$$

The relationship between the two response variables is represented by the odds ratio parameter θ, defined as follows in Eq. (3) [5]:

$$\theta = \frac{p_{11}p_{00}}{p_{10}p_{01}} \tag{3}$$

where:

- $p_{11} = P(Y_1 = 1, Y_2 = 1)$,
- $p_{10} = P(Y_1 = 1, Y_2 = 0)$,
- $p_{01} = P(Y_1 = 0, Y_2 = 1)$,
- $p_{00} = P(Y_1 = 0, Y_2 = 0)$.

The joint probability distribution of the two binary response variables can be written as shown in Eq. (4):

$$P(Y_{1i} = y_{1i}, Y_{2i} = y_{2i}) = p_{11i}^{y_{1i}y_{2i}} p_{10i}^{y_{1i}(1-y_{2i})} p_{01i}^{(1-y_{1i})y_{2i}} p_{00i}^{(1-y_{1i})(1-y_{2i})} \tag{4}$$

subject to the constraint given in Eq. (5):

$$p_{11} + p_{10} + p_{01} + p_{00} = 1 \tag{5}$$

In this study, the predictor variables used in the bivariate binary logistic regression model are age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate. The model is implemented using the `vglm()` function with the `binom2.or()` family from the VGAM package in R to jointly model hypertension and obesity while accounting for the dependence between the two responses.

When $\theta \neq 1$, the joint probability of both events occurring simultaneously (p_{11i}) cannot be obtained by simple multiplication. Instead, it must be analytically solved as the roots of a quadratic equation derived from the odds ratio definition:

$$p_{11i} = \frac{1 + (p_{1i} + p_{2i})(\theta - 1) - \sqrt{[1 + (p_{1i} + p_{2i})(\theta - 1)]^2 - 4\theta(\theta - 1)p_{1i}p_{2i}}}{2(\theta - 1)} \tag{6}$$

Once p_{11i} is determined via Eq. (6), the remaining cellular joint probabilities are systematically computed through marginal subtractions:

$$p_{10i} = p_{1i} - p_{11i} \tag{7}$$

$$p_{01i} = p_{2i} - p_{11i} \tag{8}$$

$$p_{00i} = 1 - p_{1i} - p_{2i} + p_{11i} \tag{9}$$

2.6. Parameter Estimation and Hypothesis Testing

Parameter estimation for the bivariate binary logistic regression model is performed using Maximum Likelihood Estimation (MLE) [12]. The log-likelihood function $L(\gamma)$, given in Eq. (10), is constructed by expanding the joint probability distribution defined in Eq. (4) across all four mutually exclusive response outcomes [5]:

$$\begin{aligned} \log L(\gamma) = \sum_{i=1}^{n} [&y_{1i}y_{2i}\log(p_{11i}) + y_{1i}(1 - y_{2i})\log(p_{10i}) \\ &+ (1 - y_{1i})y_{2i}\log(p_{01i}) + (1 - y_{1i})(1 - y_{2i})\log(p_{00i})] \end{aligned} \tag{10}$$

where $\gamma = [\beta_1^T, \beta_2^T, \log\theta]^T$. Because the resulting likelihood equations do not have a closed-form solution, parameter estimation is performed iteratively using the Fisher Scoring algorithm [12]. In this study, estimation is implemented using the `vglm()` function with the `binom2.or()` family from the `VGAM` package in `R`.

The statistical significance of the estimated coefficients was evaluated using the Wald test [12]. The effect sizes were interpreted using Odds Ratios (OR), which are obtained via the exponential transformation of the estimated coefficients ($OR = e^{\beta_j}$), accompanied by their 95% confidence intervals to evaluate the specific risk contribution of each predictor.

2.7. Model Diagnostic

2.7.1. Multicollinearity (VIF)

Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated, which can lead to unstable and unreliable parameter estimates. To detect multicollinearity, the Variance Inflation Factor (VIF) was computed for each predictor variable. The VIF for the j-th predictor variable is defined as shown in Eq. (11):

$$VIF_j = \frac{1}{1 - R_j^2} \tag{11}$$

where R_j^2 is the coefficient of determination obtained from regressing the j-th predictor variable on all remaining predictor variables. A VIF value below 5 indicates no serious multicollinearity [12], while a VIF value exceeding 10 indicates a severe multicollinearity problem [12]. In this study, VIF values were computed using the `vif()` function from the `car` package in R.

2.7.2. Chi-square Dependence Test

Prior to applying the bivariate binary logistic regression model, the statistical dependence between the two response variables—hypertension and obesity—was examined using Pearson's Chi-square test with Yates' continuity correction, which is conventionally applied to 2×2 contingency tables to adjust for the discreteness of the observed frequencies. This test evaluates whether the two binary variables are independent or associated. The test statistic is defined as:

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(|O_{ij} - E_{ij}| - 0.5)^2}{E_{ij}}$$

2.7.3. Goodness-of-Fit Assessment

The Hosmer–Lemeshow (HL) test was initially considered to assess model calibration [12]. The HL test statistic follows a chi-square distribution (χ^2) with $g - 2$ degrees of freedom, where g is the number of groups. However, the HL test is strictly dependent on sample size; in large datasets (such as $n = 12,592$ in this study), the test is known to be overly sensitive. Even trivial and practically insignificant deviations between the observed and predicted probabilities will inflate the χ^2 statistic, inevitably leading to a rejection of the null hypothesis despite adequate model calibration.

Consequently, relying solely on the Hosmer-Lemeshow goodness-of-fit statistic is methodologically flawed for this dataset. Instead, to complement the predictive assessment and evaluate the agreement between predicted probabilities and observed outcomes, the Brier score was calculated as a more robust calibration measure. Furthermore, the structural appropriateness of the bivariate framework versus the independent univariate models is evaluated predominantly through relative fit indices, specifically the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which penalize model complexity appropriately.

2.7.4. Linearity Assumption

The linearity assumption for all continuous predictors on the logit scale was evaluated using the Box-Tidwell test. This procedure involves incorporating interaction terms between each continuous predictor and its natural logarithm into the regression model. A significant p-value for these interaction terms indicates a potential violation of the linearity assumption.

2.8. Model Comparison (AIC and BIC)

To evaluate whether the bivariate binary logistic regression model provides a better fit compared to the separate univariate models, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used. These criteria balance model fit and complexity, where lower values indicate a more parsimonious and better-fitting model.

The AIC is defined as shown in Eq. (12):

$$AIC = -2\ell(\hat{\beta}) + 2p \tag{12}$$

The BIC is defined as shown in Eq. (13):

$$BIC = -2\ell(\hat{\beta}) + p\ln(n) \tag{13}$$

where:

- $\ell(\hat{\beta})$ is the maximized log-likelihood of the model,

- p is the number of estimated parameters,
- n is the number of observations.

For the univariate approach, the AIC and BIC values of the two separate models were summed to obtain a combined criterion for comparison with the bivariate model [13, 14].

To evaluate model fit, AIC and BIC were computed for both approaches. These criteria differ in their penalty structure: AIC applies a penalty of $2p$, making it more appropriate when the objective is to capture underlying data structure and dependence, whereas BIC applies a stronger penalty of $p\ln(n)$, favoring parsimony and performing better under model selection in large samples [13, 14].

In this study, the primary objective is to accurately model the joint occurrence and dependence structure between hypertension and obesity. Given the large sample size ($n = 12,592$), model selection was primarily based on the Akaike Information Criterion (AIC) [13] and the Bayesian Information Criterion (BIC) [14], both of which are widely used to balance model fit and complexity. As demonstrated in the model evaluation, both AIC and BIC favored the joint bivariate model over the separate univariate models. Therefore, the inclusion of the dependence parameter θ is justified not only by the epidemiological relationship between hypertension and obesity but also by established model selection criteria, indicating that the bivariate approach provides a more parsimonious and better-fitting representation of the data without unnecessary model complexity.

2.9. Cross-Validation Procedure

To assess out-of-sample predictive performance and compare the univariate and bivariate approaches, 10-fold cross-validation was applied to the complete-case sample (n = 12,592). The data were randomly divided into 10 approximately equal folds, with nine used for training and one for testing in each iteration. Both approaches were fitted on identical training partitions using the same random seed, enabling paired out-of-sample comparisons. For the bivariate model, marginal probabilities were reconstructed from the fitted joint probabilities as $\hat{p}1 = \hat{p}10 + \hat{p}11$ and $\hat{p}2 = \hat{p}01 + \hat{p}11$, consistent with Eq. (7)–Eq. (9). For the univariate approach, two separate logistic models were refitted on each training partition. Accuracy and AUC-ROC were evaluated on the held-out folds, with fold-level AUC differences compared using paired t-tests and Wilcoxon signed-rank tests as a robustness check.

2.10. Functional-Form Validation Protocol

To justify retaining the linear specification despite the non-linearity detected in Section 2.7.4, a short criterion-based protocol was applied, combining spline modeling with formal model-comparison statistics:

1. Fit the bivariate model under linear and natural cubic spline (3 df) specifications; record AIC, BIC, and $\hat{\theta}$ for both.
2. Compare specifications via ΔAIC, ΔBIC, and a likelihood-ratio test.
3. Assess practical equivalence via the correlation between predicted probabilities, $r(\hat{p}_L, \hat{p}_S)$, and the 0.5-threshold reclassification rate.
4. Retain the linear specification if $\hat{\theta}$ is stable across specifications and $r \geq 0.95$ with reclassification below 5%, provided the retained specification does not materially alter the study's primary inferential conclusions. Where BIC decisively favors the spline model [15] for an individual outcome but the stability and equivalence conditions above are satisfied, the linear specification may still be retained for comparability across outcomes, with the discrepancy reported explicitly as a limitation.

Results of applying this protocol are reported in Section 3.

3. Results and Discussion

To understand the characteristics of the data, descriptive statistical analysis is required. The aim is to provide an overview of the data distribution for each variable. In this study, the response variables analyzed are hypertension and obesity, and the data representation is as follows.

Table 2: Percentage of response variables

Response Variable	Category	Frequency	Percentage (%)
Hypertension	Yes	5,217	41.43
Hypertension	No	7,375	58.57
Obesity	Yes	4,633	36.79
Obesity	No	7,959	63.21

Based on Table 2, 41.43% of respondents were classified as hypertensive, while 58.57% were non-hypertensive. The higher prevalence of hypertension compared to obesity suggests that hypertension is influenced not only by obesity but also by other demographic and physiological factors, including age, sex, waist circumference, lung capacity, handgrip strength, and pulse rate. The coexistence of hypertension and obesity further supports the use of bivariate binary logistic regression to jointly model these correlated response variables.

Descriptive statistics were also generated for the predictor variables, namely age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate. Their distributions, based on established clinical and demographic thresholds, are presented in Table 3.

Table 3: Descriptive statistics of predictor variables (n = 12,592)

Variable	Category	Frequency (n)	Percentage (%)
Age	33–45 years	3,598	28.57
	46–60 years	5,974	47.44
	>60 years	3,020	23.99
Sex	Male	6,091	48.37
	Female	6,501	51.63
Waist Circumference	Normal	6,629	52.65
	High	5,963	47.35
Handgrip Strength	Normal	8,059	64.00
	Low	4,533	36.00
Lung Capacity	Normal	6,367	50.56
	Low	6,225	49.44
Pulse Rate	Normal	12,273	97.47
	High	319	2.53

As shown in Table 3, the sample consists of a relatively balanced proportion of male (48.51%) and female (51.49%) respondents. The majority of the respondents fall into the 46–60 years age group (47.44%). Regarding physiological indicators, waist circumference and lung capacity demonstrate a nearly equal distribution between normal and at-risk categories. Conversely, the vast majority of the respondents exhibited a normal pulse rate (97.47%), indicating that extreme resting heart rates are rare within this study population.

Table 4: Variance Inflation Factor (VIF) values for predictor variables

Variable	VIF (Hypertension Model)	VIF (Obesity Model)
Age	1.528	1.456
Sex	2.332	2.687
Waist Circumference	1.108	1.134
Handgrip Strength	2.709	2.856
Lung Capacity	1.939	2.048
Pulse Rate	1.045	1.023

Prior to fitting the logistic regression models, a multicollinearity diagnostic was conducted to ensure the independence of the predictor variables. Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, which can inflate the standard errors of the coefficient estimates, render them statistically unstable, and consequently obscure the true independent effect of each predictor on the response variable. This diagnostic was quantitatively evaluated using the Variance Inflation Factor (VIF), which measures the extent to which the variance of an estimated regression coefficient is increased due to collinearity. A commonly accepted statistical rule of thumb suggests that a VIF value exceeding 5 or 10 indicates problematic multicollinearity that requires remediation. As presented in Table 4, the computed VIF values for all predictors—age, sex, waist circumference, handgrip strength, lung capacity, and pulse rate—ranged between approximately 1.02 and 2.86 across both the hypertension and obesity models. Since these values are well below the conservative threshold of 5, it can be concluded that there is no severe multicollinearity present among the independent variables. Consequently, the stability of the parameter estimates is mathematically preserved, and all selected predictor variables were confidently retained for the subsequent regression analyses without the need for variable exclusion or dimensionality reduction.

Following the multicollinearity diagnostic, the linearity assumption for continuous predictors on the logit scale was assessed using the Box–Tidwell test. Significant departures from linearity were observed for age ($p < 0.001$), handgrip strength ($p < 0.001$), pulse rate ($p < 0.001$), and waist circumference ($p = 0.010$) in the hypertension model, and for waist circumference ($p < 0.001$), age ($p = 0.041$), and lung capacity ($p = 0.017$) in the obesity model. Given the large sample size ($n = 12{,}592$), to rigorously address whether these deviations represent clinically meaningful non-linearity or are merely artifacts of high statistical power, a formal sensitivity analysis utilizing natural cubic splines was conducted, following the functional-form validation protocol described in Section 2.10. The detailed results of this sensitivity analysis, alongside the justification for retaining the linear specification, are presented subsequently in the model comparison section.

Table 5: Prevalence of Obesity by Hypertension Status

Hypertension	Obesity (Yes)	Obesity (No)	Total
Yes	2,295 (44.0%)	2,922 (56.0%)	5,217
No	2,338 (31.7%)	5,037 (68.3%)	7,375
Total	4,633	7,959	12,592

The joint frequency distribution presented in Table 5 highlights the co-occurrence of both conditions within the sample. Specifically, 2,295 respondents suffered from both hypertension and obesity simultaneously, representing a substantial subset of the population and necessitating an evaluation of their statistical dependence.

Table 6: Pearson Chi-square test of association

Test	Value
Chi-square	197.9
p-value	< 0.001

Furthermore, the relationship between hypertension and obesity was formally examined using the Pearson Chi-square test (Table 6). The analysis produced a notably large Chi-square test statistic of 197.93, with a p-value of less than 0.001. Since this p-value falls decisively below the 0.01 significance level, the null hypothesis of independence is strongly rejected. This provides overwhelming empirical evidence that hypertension and obesity are not isolated physiological events but are highly interdependent conditions within this population. From a statistical modeling perspective, this profound dependence suggests that analyzing these variables separately through standard univariate logistic regression may not fully capture the inherent correlation structure between the outcomes. Therefore, the application of Bivariate Binary

Logistic Regression provides a more comprehensive framework to simultaneously and accurately evaluate the shared predictors of these two correlated diseases.

The parameter estimates, standard errors, z-values, p-values, and Odds Ratios (OR) for the univariate binary logistic regression model predicting hypertension are presented in Table 7.

Table 7: Parameter estimation of univariate binary logistic regression for hypertension

Predictor Variable	Estimate (β)	Std. Error	z-value	p-value	Odds Ratio (OR)
Intercept	-9.1075	0.2822	-32.278	< 0.001	0.000
Age	0.0619	0.0023	26.567	< 0.001	1.064
Sex (Female)	0.2126	0.0595	3.572	0.0004	1.237
Waist Circumference	0.0371	0.0018	20.449	< 0.001	1.038
Handgrip Strength	0.0124	0.0036	3.443	0.0006	1.012
Lung Capacity	-0.0004	0.0002	-1.715	0.086	1.000
Pulse Rate	0.0262	0.0018	14.823	< 0.001	1.027

Based on the parameter estimates in Table 7, the fitted univariate binary logistic regression model for hypertension can be written as follows:

$$\text{logit}\left[\pi_1(\mathbf{x})\right] = -9.1075 + 0.0619X_1 + 0.2126X_2 + 0.0371X_3 + 0.0124X_4 - 0.0004X_5 + 0.0262X_6$$

where $\pi_1(\mathbf{x})$ is the probability of a respondent having hypertension, X_1 is age, X_2 is sex (1 if female, 0 if male), X_3 is waist circumference, X_4 is handgrip strength, X_5 is lung capacity, and X_6 is pulse rate. The univariate analysis reveals that almost all selected predictor variables are significantly associated with hypertension at the 5% significance level, with the notable exception of lung capacity ($p = 0.086$). Age exhibits a positive and significant effect on the probability of developing hypertension, where each additional year of age increases the odds of hypertension by 6.4% ($OR = 1.064$). Sex is also a critical determinant; female respondents in this population have 23.7% higher odds of experiencing hypertension compared to their male counterparts ($OR = 1.237$).

Furthermore, central adiposity, as measured by waist circumference, demonstrates a highly significant positive association. Every one-centimeter increase in waist circumference elevates the odds of hypertension by 3.8% ($OR = 1.038$), affirming the established clinical understanding that abdominal obesity is a primary risk factor for elevated blood pressure. Finally, handgrip strength and pulse rate both show statistically significant positive effects: each one-kilogram increase in handgrip strength raises the odds of hypertension by 1.2% (OR = 1.012), and each one-beat-per-minute increase in pulse rate raises the odds by 2.7% (OR = 1.027).

Similarly, the parameter estimates, standard errors, z-values, p-values, and Odds Ratios (OR) for the univariate binary logistic regression model predicting obesity are detailed in Table 8.

Table 8: Parameter estimation of univariate binary logistic regression for obesity

Predictor Variable	Estimate (β)	Std. Error	z-value	p-value	Odds Ratio (OR)
Intercept	-21.9700	0.5270	-41.685	< 0.001	0.000
Age	-0.0561	0.0036	-15.377	< 0.001	0.945
Sex (Female)	1.5490	0.0946	16.383	< 0.001	4.708
Waist Circumference	0.2595	0.0049	52.799	< 0.001	1.296
Handgrip Strength	0.0255	0.0053	4.784	< 0.001	1.026
Lung Capacity	0.0015	0.0003	4.240	< 0.001	1.001
Pulse Rate	-0.0005	0.0026	-0.191	0.849	1.000

Based on the parameter estimates in Table 8, the fitted univariate binary logistic regression model for obesity is formulated as follows:

$$\begin{aligned}\text{logit}\left[\pi_2(\mathbf{x})\right] = &-21.9700 - 0.0561X_1 + 1.5490X_2 + 0.2595X_3 + 0.0255X_4 \\ &+ 0.0015X_5 - 0.0005X_6\end{aligned}$$

where $\pi_2(\mathbf{x})$ denotes the probability of a respondent being obese.

The univariate analysis for obesity reveals a distinct predictor profile compared with hypertension. Pulse rate was not significantly associated with obesity ($p = 0.849$), suggesting that resting heart rate does not directly predict general adiposity in this model. In contrast, age showed a significant negative association, with each additional year reducing the odds of obesity by approximately 5.5% ($OR = 0.945$). This inverse relationship may reflect age-related physiological changes, including declining muscle mass, or survivorship bias in the surveyed IFLS5 population.

Sex was a strong predictor, with female respondents having substantially higher odds of obesity than males ($OR = 4.708$), consistent with differences in fat distribution, hormonal profiles, and physical activity patterns. Waist circumference was also a dominant predictor, with each one-centimeter increase associated with a 29.7% increase in obesity odds ($OR = 1.296$). Handgrip strength and lung capacity were statistically significant ($p < 0.001$), but their effects were small: each one-kilogram increase in handgrip strength increased the odds by 2.6% ($OR = 1.026$), while each one-liter increase in lung capacity increased the odds by only 0.1% ($OR = 1.001$). These findings highlight the distinction between statistical significance and practical clinical relevance in large samples.

Table 9: Bivariate binary logistic regression model

Variable	Estimate	Std. Error	z-value	p-value	OR	95% CI
Hypertension Model						
Intercept	-9.1070	0.2823	-32.264	< 0.001	–	–
Age	0.0619	0.0023	26.558	< 0.001	1.064	1.059–1.069
Sex (Female)	0.2126	0.0595	3.572	0.0004	1.237	1.101–1.390
Waist circumference	0.0371	0.0018	20.412	< 0.001	1.038	1.034–1.042
Handgrip strength	0.0124	0.0036	3.438	0.0006	1.012	1.005–1.020
Lung capacity	-0.0004	0.0002	-1.720	0.085	1.000	0.999–1.000
Pulse rate	0.0262	0.0018	14.827	< 0.001	1.027	1.023–1.030
Obesity Model						
Intercept	-21.9600	0.5267	-41.691	< 0.001	–	–
Age	-0.0562	0.0036	-15.403	< 0.001	0.945	0.939–0.952
Sex (Female)	1.5530	0.0946	16.423	< 0.001	4.725	3.926–5.687
Waist circumference	0.2596	0.0049	52.821	< 0.001	1.296	1.284–1.309
Handgrip strength	0.0255	0.0053	4.787	< 0.001	1.026	1.015–1.037
Lung capacity	0.0015	0.0003	4.252	< 0.001	1.001	1.001–1.002
Pulse rate	-0.0007	0.0026	-0.258	0.796	0.999	0.994–1.004
Dependence Parameter						
Association, $\log(\theta)$	0.2299	0.0613	3.753	0.000175	$1.258^{\dagger}$	1.116–1.419

†Reported as $\theta = \exp(\log\theta)$; the odds ratio interpretation applies to θ, not to the estimate column, which reports $\log\theta$.

The bivariate binary logistic regression model can be written as follows: For hypertension:

$$\text{logit}(\pi_1) = -9.1070 + 0.0619X_1 + 0.2126X_2 + 0.0371X_3 + 0.0124X_4 - 0.0004X_5 + 0.0262X_6$$

For obesity:

$$\text{logit}(\pi_2) = -21.9600 - 0.0562X_1 + 1.5530X_2 + 0.2596X_3 + 0.0255X_4 + 0.0015X_5 - 0.0007X_6$$

where:

- π_1 = probability of hypertension occurrence,
- π_2 = probability of obesity occurrence,
- X_1 = age,
- X_2 = sex,
- X_3 = waist circumference,
- X_4 = handgrip strength,

- X_5 = lung capacity,
- X_6 = pulse rate.

In addition, the dependence parameter between hypertension and obesity, as defined in Eq. (3), was estimated as:

$$\log\theta = 0.2299$$

with:

$$\theta = e^{0.2299} = 1.258$$

The dependence parameter $\theta = 1.258$ ($p < 0.001$) indicates a highly significant positive association between hypertension and obesity. It must be strictly emphasized that within the bivariate binary logistic framework, θ represents a symmetric joint association parameter (global cross-ratio) capturing the co-occurrence of the two conditions [16]. It should not be interpreted as a causal mechanism or a direct conditional effect of one disease upon the other. While epidemiological literature often attributes this bidirectional co-occurrence to shared pathophysiological mechanisms, from a statistical modeling perspective, the significance of this θ parameter robustly justifies the structural necessity of jointly modeling these outcomes rather than treating them as independent univariate events.

To explicitly address potential selection bias arising from the complete-case analysis—which effectively restricted the sample to respondents aged 33 years and older—a sensitivity analysis was conducted by stratifying the sample into two age subgroups (33-49 years and ≥ 50 years). The estimated dependence parameter remained remarkably stable across both cohorts ($\theta = 1.262$ for ages 33–49, $n = 5{,}559$; $\theta = 1.253$ for ages ≥ 50, $n = 7{,}033$), closely mirroring the overall sample estimate ($\theta = 1.258$) . This consistency demonstrates that the positive association between hypertension and obesity is structurally robust and not an artifact of the age restriction within the observed data.

Table 9 reveals distinct effect patterns across the predictor variables for hypertension and obesity. Evaluating both the statistical significance (z-value) and effect size (Odds Ratio) provides a comprehensive understanding of each predictor's contribution to the two outcomes. Advancing age emerged as the most prominent statistical determinant for hypertension ($z = 26.558$, $OR = 1.064$), while simultaneously reducing the odds of obesity ($OR = 0.945$), consistent with vascular aging theory and age-related body mass reduction among elderly populations [8, 17]. Female respondents exhibited higher odds of both hypertension and obesity than males, likely reflecting hormonal differences, lower basal metabolic rates, and fat redistribution patterns [17, 18]. Conversely, waist circumference was the dominant physiological predictor for obesity ($z = 52.821$, $OR = 1.296$) and remained a highly significant secondary predictor for hypertension ($z = 20.412$, $OR = 1.038$) [1, 8]. This robust statistical association supports the clinical consensus that central adiposity promotes insulin resistance, chronic inflammation, and sympathetic nervous system activation, thereby increasing cardiovascular risk [19, 20].

This pattern is consistent with a classical suppression effect in multiple regression, where the inclusion of correlated predictors (particularly waist circumference and sex) alters the estimated direction or magnitude of another predictor's coefficient [21]. In this context, absolute handgrip strength is known to correlate positively with body size and muscle mass — both of which are also associated with larger waist circumference. Once waist circumference is controlled, the residual variance in handgrip strength may reflect physical frame size rather than true muscular fitness, producing a spurious positive direction.

This finding highlights a methodological limitation of using absolute handgrip values without standardization by body weight or BMI, as recommended in recent literature [22]. Future studies should consider using relative handgrip strength (handgrip/BMI or handgrip/body weight) to more accurately capture muscular fitness independent of body size.

Regarding lung capacity, the analysis revealed a negligible, non-significant negative association with hypertension ($p = 0.085$), indicating no true protective effect within this sample. Conversely, it demonstrated a marginally positive, albeit statistically significant, association with obesity ($p < 0.001$, $OR = 1.001$). This latter finding is likely a methodological artifact, where the high statistical significance is driven primarily by the massive statistical power of the large sample size ($n = 12,592$) rather than a clinically meaningful effect, considering that absolute lung capacity without height standardization proxies physical frame size rather than true pulmonary efficiency [4]. Finally, pulse rate significantly increased hypertension odds ($OR = 1.027$) but was not significant for obesity ($p = 0.796$), consistent with its role in sympathetic nervous system activity rather than adiposity [23].

To facilitate interpretation, Fig. 1 presents the ORs with 95% CIs, complementing the results in Table 9. The vertical line at OR = 1 denotes the null effect, with CIs crossing the line indicating non-significant associations.

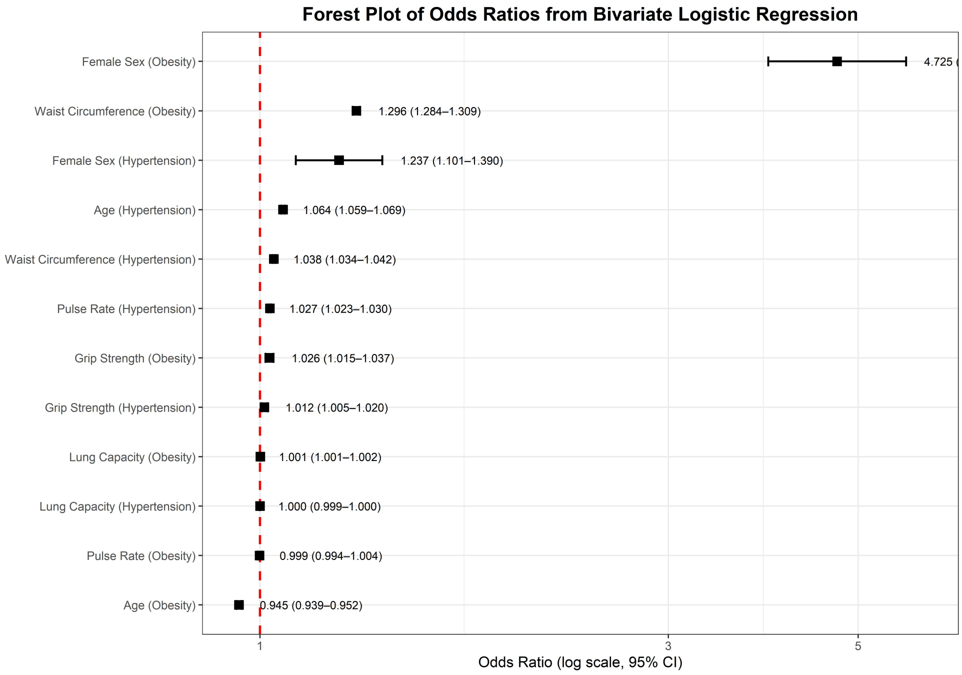

Fig. 1: Forest plot of ORs with 95% CIs. The red dashed line indicates OR = 1.

After estimating the parameters, it is necessary to compare the performance of the proposed bivariate model against the standard univariate approach. The comparison of the models' goodness-of-fit was evaluated using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). A model with lower AIC and BIC values is considered to have a better fit to the data while penalizing for unnecessary complexity.

The AIC and BIC values for the separate univariate models (combined) and the joint bivariate model are presented in Table 10.

Table 10: Comparison of Goodness-of-Fit Criteria

Model	AIC	BIC
Univariate (Combined)	23,129.63	23,233.80
Bivariate	23,118.09	23,229.70

Based on Table 10, the Bivariate Binary Logistic Regression model yields a lower AIC value (23,118.09) compared to the combined AIC of the independent univariate models (23,129.63). Furthermore, the BIC value of the bivariate model (23,229.70) is also lower than that of the univariate framework (23,233.80).

These reductions in information criteria indicate that the bivariate model achieves better relative fit than the combined univariate models. Following conventional interpretive thresholds, the AIC difference (ΔAIC $= 11.54$) represents substantial support for the bivariate model [24], whereas the BIC difference (ΔBIC $= 4.10$) constitutes only positive, rather than decisive, evidence [15], reflecting BIC's stronger penalty for the additional dependence parameter. Taken together, both criteria consistently—though not overwhelmingly—favor the bivariate framework, supporting its use as a more appropriate, though not the sole defensible, modeling approach for jointly analyzing hypertension and obesity in this dataset.

Although the spline models improved model fit by AIC (hypertension: ΔAIC $= 30.61$; obesity: ΔAIC $= 132.03$), the BIC—which penalizes model complexity more heavily and is more appropriate for this sample size—showed a markedly different pattern (hypertension: ΔBIC $= 0.85$; obesity: ΔBIC $= 102.27$), indicating that the nonlinearity detected in the hypertension model was largely attributable to the statistical power of the large sample rather than a substantial structural effect, whereas the obesity model showed strong evidence of genuine nonlinearity by both criteria. A formal likelihood ratio test comparing the fully linear and spline-specified bivariate models confirmed that the improvement in fit was statistically significant overall ($\chi^2 = 177.96$, $df = 8$, $p < 0.0001$).

Table 11 summarizes the model-fit statistics and dependence parameter estimates for the linear and spline specifications.

Table 11: Comparison of Linear and Spline Model Specifications

Specification	Biv. AIC	Biv. BIC	Uni. AIC	Uni. BIC	θ (95% CI)
Linear	23,118.09	23,229.70	23,129.63	23,233.80	1.258 (1.116–1.419)
Spline (age, waist; 3 df each)	22,956.13	23,127.27	22,966.98	23,130.68	1.251 (1.106–1.415)

Nevertheless, the dependence parameter remained materially unchanged under the spline specification ($\theta = 1.251$, 95% CI: 1.106–1.415, versus $\theta = 1.258$, 95% CI: 1.116–1.419), with highly correlated predicted probabilities (hypertension: $r = 0.991$; obesity: $r = 0.998$) and low reclassification rates (3.9% and 1.2%, respectively). The bivariate model also continued to outperform the combined univariate models under both specifications (ΔAIC $= 10.85$–11.54, ΔBIC $= 3.41$–4.10), confirming that the central conclusion regarding joint dependence is not an artifact of functional-form misspecification. Notably, BIC decisively favored the spline specification for obesity in isolation (ΔBIC $= 102.27$), exceeding the retention threshold in Step 4 of Section 2.10. This exception was accepted because θ—the primary inferential target—remained stable, and the high predictive equivalence ($r = 0.998$, reclassification $= 1.2\%$) indicated no materially different substantive model. The linear specification was therefore retained for both outcomes to preserve comparability, with the spline model reported as a robustness check and the decisive, though predictively modest, nonlinearity in the obesity model acknowledged as a limitation.

Finally, to evaluate the predictive performance and discriminative ability of the selected bivariate binary logistic regression model, the classification accuracy and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) were calculated for both response variables. The summary of these predictive metrics is presented in Table 12.

Table 12: Classification accuracy and AUC of the Bivariate Binary Logistic Regression model

Condition	**Classification Accuracy (%)**	**AUC**
Hypertension	66.72	0.716
Obesity	86.75	0.937

Classification accuracy was evaluated using a 0.5 probability threshold. Based on the reconstructed marginal probabilities, the bivariate model correctly classified 86.75% of obesity cases and 66.72% of hypertension cases, with both values exceeding their respective no-information rates. The Area Under the Receiver Operating Characteristic Curve (AUC) was additionally used as a threshold-independent measure, together indicating satisfactory predictive performance.

Furthermore, a 10-fold cross-validation was conducted to assess predictive performance and potential overfitting. The bivariate model achieved mean out-of-sample AUCs of 0.715 (SD = 0.014) for hypertension and 0.937 (SD = 0.005) for obesity. Paired t-tests and Wilcoxon signed-rank tests showed no significant differences in AUC for either hypertension ($p = 0.780$) or obesity ($p = 0.678$), indicating that although the bivariate model provided a better overall fit (lower AIC/BIC) and explicitly captured outcome dependence, it did not improve marginal discriminative performance over separate univariate models.

To visually demonstrate the discriminative ability of the bivariate model, the Receiver Operating Characteristic (ROC) curves for both the hypertension and obesity models are plotted in Fig. 2.

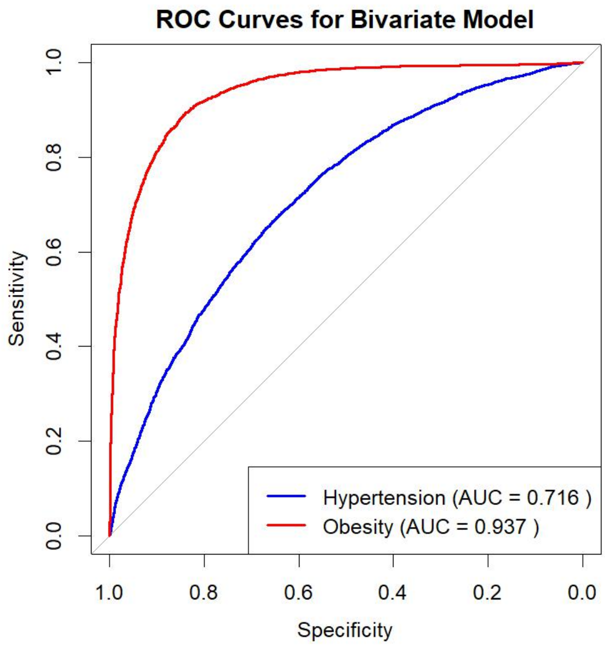

Fig. 2: ROC curves of the bivariate binary logistic regression model for hypertension and obesity.

Fig. 2 presents the ROC curves corresponding to the calculated AUC values, with Sensitivity (True Positive Rate) plotted against Specificity on the reversed x-axis, which is equivalent to the False Positive Rate. The obesity model showed excellent discrimination, with the ROC curve approaching the upper-left corner and an AUC of 0.937. This indicates a high ability of the physiological predictors to distinguish between obese and non-obese individuals.

In comparison, the hypertension model showed moderate discrimination, with an AUC of 0.716. The lower discriminative performance may reflect the multifactorial nature of hypertension, which is influenced by additional factors such as dietary sodium intake, stress, and family history that were not included in the model.

A sensitivity analysis was also conducted by excluding waist circumference to address potential construct circularity. Removing this predictor substantially reduced the obesity model's AUC from 0.937 to 0.706. This result indicates that the high discriminative performance of the original obesity model was strongly influenced by the physiological relationship between waist circumference and the BMI-based definition of obesity.

Model calibration was further assessed using the Brier score. The bivariate model yielded a Brier score of 0.0945 for obesity and 0.2100 for hypertension. For hypertension, the Brier score was lower than the no-skill baseline of 0.2427, indicating better predictive performance than the prevalence-based baseline. Overall, the results demonstrate strong discrimination and calibration for obesity, while the hypertension model showed moderate discrimination with adequate predictive performance.

4. Conclusion

This study compared univariate and bivariate binary logistic regression models using IFLS5 data ($n = 12,592$) to jointly analyze hypertension and obesity. A highly significant positive dependence was observed between the two outcomes ($\theta = 1.258$, $p < 0.001$), confirming the structural importance of modeling them jointly rather than as independent conditions. Advancing age emerged as the strongest determinant of hypertension, whereas waist circumference was the dominant physiological predictor of obesity.

Model comparison showed that the bivariate binary logistic regression model provided a modestly better overall fit than the combined univariate models, as reflected by lower AIC and BIC values. Although the improvement in predictive discrimination (AUC) over separate univariate models was limited, the bivariate framework demonstrated satisfactory calibration and provided additional statistical value by explicitly capturing the dependence between hypertension and obesity.

Sensitivity analyses further confirmed that the estimated dependence was robust across age subgroups and that the strong predictive contribution of waist circumference reflected the role of central adiposity rather than construct circularity with the BMI-based obesity definition.

Methodologically, this study also contributes a criterion-based functional-form validation protocol (Section 2.10) that integrates spline modeling, AIC/BIC comparison, and a likelihood-ratio test into a reproducible decision rule for bivariate binary logistic regression, applicable beyond the present hypertension–obesity context.

Nevertheless, because the analysis was based on cross-sectional IFLS5 data and the complete-case sample was restricted by survey-design-driven missingness, these findings should be interpreted as structural associations rather than causal relationships. Future research should incorporate additional lifestyle-related covariates, such as physical activity and dietary factors, and explore alternative multivariate approaches for jointly modeling correlated binary health outcomes.

CRediT Authorship Contribution Statement

Muhamad Lazuardi: Conceptualization, Methodology, Data Curation, Formal Analysis, Software, Visualization, Writing–Original Draft Preparation, Writing–Review & Editing.
A'yunin Sofro: Supervision, Validation, Writing–Review & Editing.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools were used during the preparation of this manuscript for language refinement, LaTeX formatting assistance, and manuscript structuring. All scientific interpretation, statistical analysis, model development, and final manuscript verification were conducted entirely by the authors.

Declaration of Competing Interest

The authors declare no competing interests.

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Data and Code Availability

Raw IFLS5 data are not redistributed in this repository, in accordance with the data use agreement of RAND Corporation, which prohibits redistribution of IFLS Public Use data to third parties. Interested researchers may obtain the data directly by registering at: https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS.html

The complete data-cleaning and analysis code is publicly available at: https://github.com/mlazuardi77/A_Comparative_Study_of_Univariate_and_Bivariate_Logistic_Regression_on_Hypertension_and_Obesity-

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