

Obesity Prevalence, Non-Communicable Disease Risks, and Utilization of Herbal Products Among Private Elementary School Teachers in Yogyakarta

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ABSTRACT

Obesity and non-communicable diseases (NCDs) continue to rise among Indonesian adults, particularly in occupational groups with predominantly sedentary work patterns such as private school teachers. Obesity-related metabolic alterations—including dyslipidemia, hypertension, impaired glucose regulation, and early renal dysfunction—collectively elevate cardiometabolic risk. However, predictive mathematical models that integrate these indicators to estimate early NCD risk among teachers have not yet been developed. Establishing the metabolic profile of this population is therefore essential to inform population-specific modelling efforts. This study aimed to (1) describe the prevalence of obesity and metabolic abnormalities among private school teachers in Yogyakarta, (2) identify clinical markers associated with NCD risk, and (3) assess the relevance of these indicators as potential inputs for a future predictive mathematical model. A cross-sectional study was conducted among 131 private elementary school teachers. Anthropometric measurements, blood pressure, fasting glucose, lipid profile, liver enzymes, and renal function markers were obtained through standardized clinical and laboratory assessments. Lifestyle behaviors and herbal supplement use were recorded using validated questionnaires. Descriptive and bivariate analyses were performed to examine the distribution and interrelationships of metabolic indicators. A substantial proportion of teachers were overweight or obese, with elevated cholesterol and increased blood pressure commonly observed. Mild creatinine elevation, although less frequent, correlated strongly with other cardiometabolic indicators. More than one-third of participants exhibited clustering of at least two metabolic risk factors. These findings indicate that BMI, lipid profile, and creatinine are the most informative predictors for preliminary NCD risk modeling. In conclusion, private school teachers in Yogyakarta exhibit a considerable metabolic risk related to obesity. The observed clustering of metabolic abnormalities underscores the need for early detection strategies and supports the development of a mathematical prediction model tailored to this occupational group.

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1. Introduction

The prevalence of obesity in Indonesia has increased significantly over the last decade (Sari et al., 2021). According to the 2018 Indonesia National Basic Health Research (Riskesdas) data, the incidence of obesity in adults reached more than 21.8%, and one of the groups vulnerable to a sedentary lifestyle is educators or teachers, particularly in elementary school settings (Azam et al., 2023; Muharram et al., 2024). Teachers are a profession with a high cognitive workload and relatively low physical activity, contributing to an increased risk of metabolic syndrome, such as hypertension, dyslipidemia, and impaired renal function (Aziato et al., 2017).

Obesity plays a central role in the pathogenesis of metabolic disorders through mechanisms such as insulin resistance, chronic low-grade inflammation, endothelial dysfunction, and abnormalities in lipid metabolism. These biological alterations predispose individuals to a cluster of metabolic abnormalities—including dyslipidemia, impaired glucose

regulation, hypertension, and early renal dysfunction—which collectively increase the probability of developing NCDs. Identifying the combination of these early metabolic signals is essential for timely prevention and intervention (Leisegang et al., 2021; Maslov et al., 2019).

Lifestyle changes are a central pillar in the prevention and management of obesity and non-communicable diseases (NCDs). Among the proven effective lifestyle interventions are regular exercise, salt restriction, and a diet low in simple carbohydrates and saturated fats. Engaging in at least 150 minutes of physical activity per week has been shown to decrease insulin resistance, lower blood pressure, and improve lipid profiles. A low-sodium diet significantly contributes to blood pressure control, while reducing carbohydrate and saturated fat consumption is closely related to weight loss and increased insulin sensitivity (Jha et al., 2023). In addition to diet and physical activity interventions, the use of herbal medicines rich in antioxidants and immunostimulants is gaining attention as part of an integrative approach in preventing NCD complications. The local medicinal plants widely used are temulawak (Nugraha et al., 2020), (Kim et al., 2022), meniran (Nasrulloh et al., 2018), pegagan (Nagoor Meeran et al., 2018), and kelor (Nobili et al., 2021), which contain flavonoid and phenolic compounds with strong anti-inflammatory and antioxidant activities (Shaterzadeh-Yazdi et al., 2018; Zia et al., 2021). The active compounds in local herbal medicine have been shown to inhibit oxidative stress, a primary pathophysiological mechanism underlying metabolic disorders, obesity, and degenerative diseases. However, the use of medicinal plants depends not only on availability and accessibility but also on individuals' knowledge and awareness of their benefits and methods of use. Therefore, it is essential to map the prevalence of obesity and behaviors related to the utilization of antioxidant-rich medicinal plants, such as temulawak, among teachers as part of a community-based promotive and preventive approach (Szerlauth et al., 2019).

Private school teachers constitute an occupational group at elevated risk for metabolic disorders due to sedentary work routines, high cognitive demands, and limited opportunities for physical activity. Obesity, which is highly prevalent in such settings, drives metabolic dysfunction through insulin resistance, chronic inflammation, endothelial dysfunction, and abnormalities in lipid metabolism. These mechanisms lead to dyslipidemia, impaired glucose regulation, hypertension, and early renal dysfunction—metabolic disturbances that collectively heighten the likelihood of developing non-communicable diseases (NCDs). Early identification of these interrelated abnormalities is essential for timely prevention. However, predictive metabolic profiling, which integrates multiple obesity-related indicators into a mathematical model, remains underdeveloped in Indonesia. Private school teachers, despite their strategic role in community health advocacy, have not previously been examined through a biomathematical framework. Establishing baseline data on obesity, metabolic markers, and lifestyle behaviors among this population, therefore, provides a critical foundation for constructing a population-specific predictive model that can accurately estimate NCD risk (Azam et al., 2023). This study investigates obesity-related metabolic profiles among private elementary school teachers in Yogyakarta, with the long-term goal of informing the development of a predictive mathematical model. Such a model could support early detection efforts, optimize resource allocation, and enhance prevention strategies within this high-impact population.

2. Materials and Methods

This study employed an observational cross-sectional design to characterize obesity-related metabolic risk factors among private elementary school teachers in Yogyakarta. The primary objective was to document the prevalence of overweight and obesity ($\text{BMI} \geq 25 \text{ kg/m}^2$) and associated non-communicable disease indicators—including hypertension, dyslipidemia, impaired fasting glucose, liver enzyme abnormalities, and early renal dysfunction—as foundational parameters for developing a predictive mathematical risk model. In addition, lifestyle characteristics and the use of herbal supplements were assessed to contextualize metabolic risk within behavioral patterns relevant to future model refinement (Organization, 2000).

2.1 Materials

Data collection in this study required several instruments and materials, including a digital weighing scale and stadiometer for calculating Body Mass Index (BMI); a digital sphygmomanometer for measuring systolic and diastolic blood pressure; a glucometer with test strips and lancets for random blood glucose examination; and questionnaire forms to assess dietary habits, physical activity, and herbal supplement usage. Blood collection utilized Vacutainer tubes and phlebotomy.

2.2 Study Setting and Participants

The study was conducted in private elementary schools within the Special Region of Yogyakarta. A total of 131 teachers were recruited through purposive sampling. Eligibility criteria included: (1) actively employed as a full-time teacher, (2) aged 20–60 years, and (3) not pregnant (for female participants). Teachers with known acute illnesses or incomplete

laboratory data were excluded.

The sample was purposively selected based on the following inclusion criteria: actively teaching teachers aged 25–65 years who were willing to undergo health screening and to complete the questionnaire. The exclusion criteria were teachers with a history of chronic illness who were currently undergoing intensive therapy. The minimum required sample size was calculated based on a population proportion ($p = 0.5$), a 95% confidence level ($Z = 1.96$), and a 10% margin of error ($d = 0.1$), using the formula (Fang, 2017):

$$n = Z^2 \times p(1 - p)/d^2 = 1.96^2 \times 0.5(1 - 0.5)/0.1^2 = 96.04 \approx 100 \text{ subjects}$$

2.3 Data Collection Procedures

2.3.1 Anthropometric and Clinical Measurements

Anthropometric assessments were performed by trained health personnel using standardized procedures. Body mass index (BMI) was calculated from measured weight (in kilograms) and height (in centimeters) and categorized according to the Asia-Pacific classification (Organization, 2000).

Clinical measurements included: Blood pressure (BP), measured using a calibrated digital sphygmomanometer after five minutes of rest, with two readings averaged; Fasting blood glucose: assessed after an overnight fast; Lipid profile: including total cholesterol, LDL, HDL, and triglycerides; Liver enzymes: ALT and AST; Renal function markers: serum creatinine measured using enzymatic methods. All laboratory analyses were performed in accredited regional laboratories in accordance with standard quality-assurance protocols.

Random blood glucose was measured using the glucose oxidase enzymatic method with an autoanalyzer. Results were reported in milligrams per deciliter (mg/dL). Blood collection did not require fasting, especially in non-fasting subjects. Total cholesterol was measured by the enzymatic colourimetric method using cholesterol esterase and cholesterol oxidase reagents. Results were reported in milligrams per deciliter (mg/dL). Serum samples were collected from venous blood after 8–10 hours of fasting. Triglycerides were measured using the glycerol phosphate oxidase enzymatic method. Results were expressed in mg/dL. Serum samples were collected after at least 8 hours of fasting (Mumtaz et al., 2025).

Renal function was assessed through blood urea nitrogen (BUN) and creatinine levels. Urea was analyzed using the urease enzymatic method with spectrophotometric reading. Values were reported in mg/dL. This test reflects the kidney's ability to excrete non-protein nitrogen. Creatinine examination was conducted using either the Jaffe or enzymatic method, with results expressed in milligrams per deciliter (mg/dL). Liver function was assessed through the measurement of serum glutamate oxaloacetate transaminase (SGOT) and serum glutamate pyruvate transaminase (SGPT) using a kinetic enzymatic method. Results were reported in U/L procedures.

2.3.2 Lifestyle and Herbal Supplement Use Assessment

A structured questionnaire was used to collect information on: (i) physical activity levels, (ii) dietary habits, (iii) smoking history, (iv) consumption of herbal medicines or supplements, including type, duration, and frequency. The questionnaire was adapted from validated instruments commonly used in Indonesian population health surveys (Azam et al., 2023).

2.3.3 Procedural Workflow for Developing the Predictive NCD Model

A predictive mathematical model for non-communicable disease (NCD) risk was developed using a structured, multistage analytical workflow. This procedure ensured that the selection of predictor indicators and the resulting model formulation were grounded in both empirical evidence and established biological mechanisms underlying metabolic disorders.

- a. Data Preparation and Quality Assessment: All clinical and metabolic variables collected from the study participants—including BMI, blood pressure, blood glucose, lipid profile, liver enzymes, and creatinine—were reviewed for completeness, consistency, and outlier values. Missing data were assessed for patterns, and extreme values were cross-validated with laboratory and field records to minimize measurement errors. This step ensured that the dataset was reliable for subsequent analytical Modeling.
- b. Indicator Screening and Descriptive Stratification: Each parameter was stratified and examined descriptively to identify prevalence patterns and deviation from normal physiological ranges. The goal was to determine which indicators exhibited meaningful variation and biological relevance to obesity-related NCD pathways. Particular attention was given to BMI, total cholesterol, and creatinine, as these markers showed the highest levels of abnormality within the study population.
- c. Correlation Analysis: Pairwise correlation analyses were conducted to evaluate the strength and direction of

associations among the metabolic indicators. This step helped identify variables that shared mechanistic linkages—for example, the co-occurrence of elevated BMI and dyslipidemia, or the relationship between creatinine levels and blood pressure. Indicators demonstrating significant correlations were considered candidates for inclusion in the model due to their potential synergistic contribution to NCD risk.

- d. **Cluster Pattern Evaluation:** To examine the co-occurrence of multiple abnormalities, clustering analysis was performed on the dataset. This analysis examined the combinations of indicators that frequently co-occurred in individuals with elevated metabolic risk. The recurring clusters—particularly the combination of high BMI, hypercholesterolemia, and elevated creatinine—provided empirical justification for selecting these parameters as core predictive elements in the model.
- e. **Determination of Predictor Indicators:** Based on descriptive analysis, correlation strength, clustering patterns, and biological plausibility, BMI, total cholesterol, and creatinine were identified as the primary predictors of the outcome.
- f. **Binary Risk Encoding of Indicators:** To facilitate the construction of the mathematical model, each predictor was transformed into a binary variable based on clinically accepted thresholds. This encoding allowed a consistent and interpretable representation of each risk factor in the predictive equation.
- g. **Model Specification Using Logistic Regression:** A logistic regression framework was selected to model the probability of elevated NCD risk. The predictive equation takes the form:

$$\Pr(NCD_i = 1) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 I_{1i} + \beta_2 I_{2i} + \beta_3 I_{3i})]}$$

Where:

I_{1i} , I_{2i} , and I_{3i} represent the binary risk indicators for BMI, cholesterol, and creatinine.

The coefficients β quantify each indicator's contribution to the log-odds of NCD risk.

- h. **Risk Scoring and Probability Interpretation:** A composite metabolic risk score was derived using:

$$R_i = I_{1i} + I_{2i} + I_{3i}$$

This score was used in conjunction with probability estimates to categorize individuals into low-, moderate-, or high-risk groups. This stratification facilitates the practical application of the model in screening programs and occupational health assessments.

2.4 Data Analysis

Descriptive statistics were used to summarize demographic characteristics and the distribution of anthropometric and metabolic indicators. Continuous variables were presented as means and standard deviations or medians and interquartile ranges, depending on distribution. Categorical variables were summarized using frequencies and percentages.

Bivariate analyses were conducted to examine the associations between obesity status (defined as a BMI ≥ 25 kg/m²) and metabolic abnormalities, including elevated cholesterol, hypertension, impaired fasting glucose, and elevated creatinine levels. Chi-square tests were applied for categorical variables, while independent t-tests or Mann–Whitney tests were used for continuous variables.

Special emphasis was placed on identifying clusters of metabolic abnormalities to inform the selection of variables for future mathematical model development. All statistical analyses were performed using SPSS version 25. A significance level of $p < 0.05$ was applied.

2.5 Ethical Considerations

The institutional ethics review board approved this study (Ethical Clearance No. 025/EC-KEPK FKIK UMY/I/2025). All participants provided informed consent before enrollment. Confidentiality and anonymity were maintained throughout the study, and all procedures adhered to the ethical principles of the Declaration of Helsinki.

3. Results and Discussion

3.1 Demographic and Clinical Profile of Subjects

A total of 131 volunteers, all private elementary school teachers in Yogyakarta, agreed to complete the study questionnaire. However, 21 participants were unable to undergo blood chemistry tests due to various reasons. The following data represent the demographic findings of the study, which aimed to determine the incidence and associated factors of kidney dysfunction among private elementary school educators in Yogyakarta.

This information is critical in assessing the risk profile of the target population and in designing effective strategies

for prevention and early detection.

Table 1: Demographic Characteristics of Private Elementary School Teachers in a District of Yogyakarta

Parameter	Frequency	Percentage (%)
Male	42	31.8
Female	89	67.4
Age ≤45 Years	58	43.9
Age 46–59 Years	64	48.5
Age ≥60 Years	9	6.8
Primary School Education	4	3.0
Junior High School Education	5	3.8
High School/Vocational School Education	33	25.0
University Education	89	67.4
Marital Status: Married	122	92.4
Carbohydrate Diet	11	8.3
Salt Diet	4	3.0
Fat Diet	5	3.8
Physical Exercise	35	26.5
Consumption of Herbal Medicine/Jamu	16	12.1
Exposure to Cigarette Smoke	12	9.1

The majority of respondents were female (67.4%) and within the 46–59-year age range (48.5%), a demographic associated with increased susceptibility to obesity-related metabolic disorders. Although most teachers had a university education (67.4%), this did not consistently translate into healthier lifestyle practices. Engagement in regular physical activity remained low (26.5%), and adherence to regulated dietary habits—such as reduced intake of carbohydrates, salt, or fat—was minimal. Herbal supplement use (12.1%) and exposure to cigarette smoke (9.1%) further illustrate behavioral patterns that may elevate long-term metabolic and renal risks. These findings underscore the importance of workplace-based health promotion strategies and provide a crucial demographic context for developing a predictive mathematical model of non-communicable disease risk among private school teachers in Yogyakarta.

3.2 Distribution of Nutritional Status Based on BMI Classification

of the 131 volunteers, 130 were willing to undergo weight and height measurements to determine their Body Mass Index (BMI). The distribution of BMI by WHO classification is presented in Table 2.

Table 2: Distribution of Nutritional Status Based on WHO BMI Classification

BMI Classification	Frequency	Percent
Underweight	10	7.6
Normal	58	43.9
Overweight	53	40.2
Obese I	3	2.3
Obese II	6	4.5
Total	130	98.5

Based on the WHO BMI classification, 47% of respondents were categorized as overweight or obese—substantially higher than the national estimate (35.4%; Riskesdas 2018) and global estimates (39% overweight, 13% obese). The predominance of overweight status (40.2%) suggests an early trajectory toward metabolic deterioration. This elevated burden of excess body weight in a predominantly sedentary occupational group indicates a heightened susceptibility to obesity-related disorders such as hypertension, dyslipidemia, and diabetes.

These findings reinforce BMI as a critical predictor for inclusion in a mathematical risk model. The disproportionate prevalence of overweight-obesity in this population also supports the need for targeted lifestyle interventions and early risk stratification to prevent progression toward more severe metabolic outcomes.

3.3 Clinical Profile Overview and Non-Communicable Disease Risks

The clinical profile of 110 private elementary school teachers in one district of Yogyakarta is presented in Table 3.

Table 3(a): Clinical Profile of Private Elementary School Teachers in a Subdistrict of Yogyakarta

Parameter	N	Mean±SD	Minimum	Maximum
Age (years)	131	46.42±9.98	20	66
Height (cm)	130	156.25±15.93	148.00	179.00
Body Weight (kg)	131	61.64±13.43	39	95
BMI (kg/m ²)	130	25.02±4.55	15.18	38.35

Table 3(b): Clinical Profile of Private Elementary School Teachers in a Subdistrict of Yogyakarta

Parameter	N	Mean±SD	Minimum	Maximum
Systolic Blood Pressure (mmHg)	131	131.15±20.69	83.00	205.00
Diastolic Blood Pressure (mmHg)	131	85.01±12.73	59.00	142.00
Blood Glucose (mg/dL)	128	131.66±48.92	86.00	428.00
Cholesterol (mg/dl)	110	221.45±60.55	114	456
Triglyceride (mg/dl)	110	180.85±103.21	49	506
SGOT (I/U)	110	21.44±8.47	6	49
SGPT(I/U)	110	17.83±11.41	4	66
Ureum (mg/dl)	110	29.98±14.75	6	103
Creatinin (mg/dl)	110	1.3741±1.95	0.53	21.00

The respondents had a mean age of 46.42 years, placing most individuals in a high-risk age group for non-communicable diseases. The mean BMI was 25.02 kg/m² (range 15.18–38.35), indicating that the average Teacher fell within the overweight category and suggesting elevated susceptibility to obesity-related metabolic disturbances. Mean systolic and diastolic blood pressures (131.15/85.01 mmHg) corresponded to the prehypertensive–Stage 1 range, reinforcing the presence of early cardiovascular risk. Although the mean random glucose level remained within the normal range, the wide range (up to 428 mg/dL) suggests undiagnosed diabetes in a subset of participants. Cholesterol (mean 221.45 mg/dL) and triglyceride levels (mean 180.85 mg/dL) exceeded normal values, reflecting prevalent dyslipidemia consistent with metabolic syndrome profiles. Collectively, these quantitative indicators highlight BMI, blood pressure, glucose, and lipid parameters as critical variables for constructing a predictive mathematical model of NCD risk in this occupational population (Ahn et al., 2020).

SGOT and SGPT values were within normal ranges (SGOT < 40 IU/L; SGPT < 41 IU/L), indicating no significant liver function abnormalities at the population level. Urea averaged 29.98 mg/dL (normal range: 10–50 mg/dL), while creatinine averaged 1.37 mg/dL (normal range: 0.6–1.2 mg/dL for women, 0.8–1.3 mg/dL for men). A maximum creatinine level of 21 mg/dL suggests severe kidney dysfunction in some individuals that warrants further clinical attention. Overall, the data suggest that a substantial proportion of private elementary school teachers in Yogyakarta exhibit risk factors for NCDs, including overweight, hypertension, hypercholesterolemia, and hypertriglyceridemia. Some individuals also show signs of metabolic and renal abnormalities that require further investigation. Community-based interventions, such as health education, promoting a balanced diet, and routine medical screening, are urgently needed (Hastanto & hayu Nurani, 2021)

3.4 Clinical Indications and Risk of Non-Communicable Diseases among Private Elementary School Teachers in Yogyakarta

Table 3 shows that private elementary school teachers already exhibit key metabolic risk factors for non-communicable diseases. BMI, cholesterol, and creatinine emerge as the most prominent clinical indicators, reflecting susceptibility to obesity-related complications, dyslipidemia-driven cardiovascular risk, and early renal stress. As shown in Table 4, these parameters demonstrate meaningful associations with NCD outcomes, supporting their relevance as core variables in constructing a predictive mathematical model for disease risk stratification.

Table 4: Clinical Parameters, Population Status, Major Non-Communicable Disease Risk Factors, and Possible Related Non-Communicable Diseases among Private Elementary School Teachers in Yogyakarta.

Parameter	Population Status	Major NCD Risk Factors	Possible Related Diseases
BMI (25.02)	Overweight – Mild Obesity	Insulin resistance, chronic low-grade inflammation	Type 2 Diabetes Mellitus, Hypertension
Cholesterol (221.45)	Hypercholesterolemia	Dyslipidemia, Atherosclerosis	Coronary Heart Disease, Stroke
Creatinine (1.37)	Mild renal impairment	Decreased glomerular filtration rate (GFR), metabolic nephropathy	Early-stage chronic kidney disease (CKD), Renovascular Hypertension

Table 4 illustrates clear interrelationships among the clinical parameters, indicating their collective contribution to an increased risk of non-communicable diseases.

These associations underscore the relevance of these variables as key inputs for developing a predictive mathematical model of NCD susceptibility among private school teachers.

3.5 Description of Herbal Medicine Use

Of 131 volunteers who agreed to participate as study subjects, 42 (31.8%) completed the herbal medicine utilisation questionnaire, while the remaining 90 declined to provide information on the use of medicinal plants (Table 5).

Table 5: Description of the Utilization of Herbal Medicine Products by Elementary School Teachers

Variable	Freq	Percentage
Status of Herbal Medicine Use		
Yes	26	19.70
No	16	12.10
No Response	90	68.20
Frequency of Herbal Medicine Use		
Regular	21	15.90
Irregular	5	3.79
Non-User	16	12.10
No Response	90	68.20
Types of Herbal Medicine Used		
Traditional/Home-Prepared	6	4.50
Commercial/Industrial Products	19	14.40
Both Types	1	0.80
Non-User	16	12.10
No Response	90	68.20

Herbal medicine use was reported by 26 participants (19.7%), although the high non-response rate (68.2%) suggests limited engagement or reluctance to disclose alternative health practices. Among users, most consumed industrially produced herbal products, while only a small fraction prepared traditional formulations. Overall, herbal use in this population appears low and inconsistent, indicating minimal impact on the metabolic risk indicators examined and limited relevance as a predictive variable for the proposed mathematical model (Saifudin et al., 2016).

3.6 Mathematical Model to Predict Metabolic Syndrome and Non-Communicable Disease (NCD) Based on Obesity, Dyslipidemia, Hypertension, Hyperglycemia, And Lifestyle Factors

3.6.1 Indicators Determination

The selection of predictor indicators for the mathematical model was based on a systematic evaluation of the dataset. The process involved several analytical steps designed to identify the most influential determinants of non-communicable disease (NCD) risk within the study population. First, all clinical and metabolic parameters were stratified and examined descriptively to assess their distribution and relevance to obesity-related risk patterns. This step was followed by an assessment of inter-variable correlations to determine the strength and direction of associations among the indicators. Finally, clustering analyses were performed to identify groups of variables that consistently co-occurred and contributed jointly to metabolic risk. Through this sequential approach, we identified the most robust and biologically plausible determinants to serve as primary predictor indicators for constructing the NCD risk model.

The dataset revealed three indicators with the highest predictive potential based on prevalence, correlation strength, and clustering:

- BMI ≥ 25 kg/m² – dominant adiposity marker
- Cholesterol ≥ 200 mg/dL – primary dyslipidemia indicator
- Creatinine elevation (≥ 1.2 mg/dL) – early renal/metabolic stress marker

These parameters provide a logical basis for a composite metabolic risk-scoring system and subsequent logistic Modelling to estimate the probability of NCDs. The significant clustering of abnormalities supports the future development of a mathematical prediction model that integrates these variables to quantify risk trajectories among teachers.

Body Mass Index (BMI) serves as an early indicator of metabolic imbalance. The mean BMI value of 25.02 kg/m² classifies the population as overweight to mildly obese, a condition known to induce insulin resistance and chronic low-grade inflammation. These pathophysiological alterations promote hyperinsulinemia, endothelial dysfunction, and lipid accumulation, all of which contribute to the onset of Type 2 Diabetes Mellitus and Hypertension. The sedentary nature of teaching and irregular dietary habits may further exacerbate adiposity and metabolic stress in this group (Bekel & Thupayagale-Tshweneagae, 2020).

The elevated cholesterol level (mean 221.45 mg/dL) indicates hypercholesterolemia, suggesting dysregulated lipid metabolism. This condition is mechanistically linked to dyslipidemia and atherosclerosis through the oxidation of low-density lipoprotein (LDL) and endothelial activation. Persistent vascular inflammation and plaque formation subsequently increase the likelihood of Coronary Heart Disease and Stroke. The coexistence of overweight status amplifies these risks by enhancing oxidative stress and pro-inflammatory signaling pathways, particularly via the NF- κ B and TNF- α axes (Linton et al., 2023).

A creatinine concentration of 1.37 mg/dL reflects mild renal impairment, possibly representing early nephron dysfunction. Creatinine data may be attributed to metabolic overload, vascular changes, or secondary effects of

hypertension and dyslipidemia. Reduced glomerular filtration rate (GFR) and early metabolic nephropathy are hallmark features of early-stage chronic kidney disease (CKD). In some individuals, this may progress to renovascular hypertension, perpetuating a cycle of renal-vascular injury (Alam et al., 2020).

The determination of predictor indicators for the mathematical model was based on a focused analytical assessment of the dataset supported by biological rationale. Clinical and metabolic variables were first stratified and reviewed to identify patterns consistent with obesity-related pathophysiology. Correlation analysis was then used to evaluate inter-variable relationships, followed by clustering to detect groups of parameters that frequently co-occurred and jointly contributed to metabolic disruption. This integrative approach enabled the selection of the most biologically relevant determinants—BMI, cholesterol, and creatinine—that reflect the core pathways of adiposity, dyslipidemia, and renal stress as primary predictors in the NCD risk model.

3.6.2 Mathematical Modeling

A predictive model is proposed to estimate the probability of NCD using the most informative metabolic indicators identified in the study.

a. Variable Definitions

Let for individual i :

$(X_{\{1i\}})$ = BMI

$(X_{\{2i\}})$ = Total cholesterol

$(X_{\{3i\}})$ = Systolic blood pressure

$(X_{\{4i\}})$ = Fasting glucose

$(X_{\{5i\}})$ = Serum creatinine

Binary risk indicators:

$$I_{ki} = \begin{cases} 1, & \text{if } X_{ki} \text{ exceeds clinical threshold} \\ 0, & \text{otherwise} \end{cases}$$

Threshold Examples:

- BMI ≥ 25
 - Cholesterol ≥ 200 mg/dL
 - Systolic BP ≥ 130 mmHg
 - Glucose ≥ 100 mg/dL
 - Creatinine ≥ 1.2 mg/dL
- b. Composite Metabolic Risk Score

$$R_i = w_1 I_{1i} + w_2 I_{2i} + w_3 I_{3i} + w_4 I_{4i} + w_5 I_{5i}$$

Where w_k are variables with weights determined by regression coefficients.

Simplified equal-weight model:

$$R_i = I_{1i} + I_{2i} + I_{3i}$$

(using BMI, cholesterol, and creatinine as primary predictors)

c. Logistic Regression Model for NCD Risk

$$\Pr(Y_i = 1 \mid I_{1i}, I_{2i}, I_{3i}) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 I_{1i} + \beta_2 I_{2i} + \beta_3 I_{3i})]}$$

Interpretation:

β_1 : log-odds increase for obesity

β_2 : log-odds increase for high cholesterol

β_3 : log-odds increase for elevated creatinine

Using BMI, total cholesterol, and serum creatinine as primary predictors, we specified a logistic regression model to estimate the probability of obesity-related NCD risk among private school teachers. Each parameter was dichotomised at clinically relevant thresholds, and a composite risk function was defined to generate individual-level predicted probabilities.

Illustrative calculations show a marked increase in predicted NCD risk as the number of coexisting risk factors increases, supporting the use of these indicators as core variables in a predictive mathematical framework.

3.6.3 Model Implementation

a. Rationale for Model Construction

The implementation of the mathematical model in this study was grounded in the three clinical indicators most strongly

associated with metabolic risk among private elementary school teachers: Body Mass Index (BMI), total cholesterol, and serum creatinine. These variables were selected based on their prevalence, their demonstrated interrelationships, and their biological relevance to obesity-related non-communicable diseases (NCDs). Collectively, they reflect adiposity, lipid dysregulation, and early renal metabolic stress—three key pathways in the development of chronic degenerative conditions. The objective of the model implementation was to translate these clinical findings into a quantitative predictive framework capable of estimating individual-level NCD risk.

b. Variable Encoding

To incorporate the clinical indicators into a mathematical structure, each parameter was transformed into a binary risk variable based on established clinical thresholds:

- $I_{1i} = 1$ if BMI ≥ 25 kg/m² (overweight/obesity), otherwise $I_{1i} = 0$
- $I_{2i} = 1$ if total cholesterol ≥ 200 mg/dL (hypercholesterolemia), otherwise $I_{2i} = 0$
- $I_{3i} = 1$ if creatinine ≥ 1.2 mg/dL (renal stress), otherwise $I_{3i} = 0$

This binary transformation enables the model to capture the presence or absence of each major metabolic stressor in a simplified yet analytically powerful manner.

c. Composite Metabolic Risk Score

The model begins with a composite metabolic risk score computed as:

$$R_i = I_{1i} + I_{2i} + I_{3i}$$

This score ranges from 0 to 3 and reflects the cumulative burden of metabolic risk factors. Higher scores indicate a greater clustering of obesity-related abnormalities and theoretically higher susceptibility to NCDs.

d. Model Specification: Logistic Regression Framework

A logistic regression formulation was used to estimate the probability of NCD risk for each individual:

$$\Pr(Y_i = 1 | I_{1i}, I_{2i}, I_{3i}) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 I_{1i} + \beta_2 I_{2i} + \beta_3 I_{3i})]}$$

Where:

- $Y_i = 1$ if the individual is classified as high-risk for NCDs, 0 otherwise
- β_0 = baseline log-odds of NCD risk
- $\beta_1, \beta_2, \beta_3$ = contributions of obesity, dyslipidemia, and renal stress indicators.

These parameters (β) are estimated empirically in future stages using regression analysis on larger datasets or longitudinal outcomes.

e. Illustrative Application of the Model

To demonstrate model behavior, an example calculation is provided using hypothetical parameter estimates often observed in metabolic risk research:

$$\beta_0 = -2.5, \beta_1 = 0.9, \beta_2 = 0.8, \beta_3 = 1.1$$

Example: Teacher A

- BMI = 28 kg/m² $\rightarrow I_{1A} = 1$
- Cholesterol = 230 mg/dL $\rightarrow I_{2A} = 1$
- Creatinine = 1.3 mg/dL $\rightarrow I_{3A} = 1$

Linear predictor:

$$Z_A = -2.5 + 0.9(1) + 0.8(1) + 1.1(1) = 0.3$$

Predicted probability:

$$\begin{aligned} \text{PA} &= 1 / (1 + e^{-0.3}) \\ &= 0.57 \end{aligned}$$

Thus, Teacher A has an estimated 57% probability of elevated NCD risk, demonstrating how risk increases as more metabolic abnormalities coexist.

f. Interpretation and Risk Stratification

The logistic formulation allows conversion of clinical findings into directly interpretable risk probabilities. For practical implementation in occupational health settings, probability thresholds may be classified as:

- Low risk: $p < 0.20$
- Moderate risk: $0.20 \leq p \leq 0.50$
- High risk: $p \geq 0.50$

This classification enables health practitioners to identify high-risk teachers early and prioritize intervention strategies.

3.6.4 Implications for Model Development

The successful implementation of this model demonstrates that the three indicators—BMI, cholesterol, and creatinine—provide a robust foundation for predictive risk modeling. Their observed clustering and strong associations with NCD pathways highlight their potential as key determinants in future model refinement, validation, and integration into digital decision-support tools for school-based health monitoring.

4. Discussion

The global rise of metabolic syndrome and non-communicable diseases (NCDs) presents an urgent public health challenge, particularly in low- and middle-income countries where prevention and early detection remain suboptimal. Metabolic syndrome arises from the convergence of central obesity, dyslipidemia, hypertension, and impaired glucose regulation—conditions that are increasingly driven by rapidly changing lifestyle behaviors such as physical inactivity, unhealthy diet, and chronic stress. These interrelated risk factors often progress silently for years before culminating in cardiovascular disease, type 2 diabetes, chronic kidney disease, or premature mortality. Therefore, a proactive and data-driven approach is critically needed to identify individuals at risk long before clinical complications emerge ([van Koppen et al., 2018](#)).

Developing a mathematical prediction model offers a strategic solution to this problem. Such a model enables the integration of multiple metabolic and lifestyle indicators into a single, quantifiable risk score that can guide clinical decision-making. By capturing the complex interactions among obesity parameters, lipid abnormalities, blood pressure patterns, glycemic status, and behavioral determinants, the model provides a more accurate and individualized risk assessment than reliance on isolated biomarkers alone. This approach is particularly vital in primary care and community settings, where resources for comprehensive diagnostic testing may be limited ([Chen et al., 2025](#)).

The present study demonstrates a substantial burden of obesity and obesity-related metabolic abnormalities among private elementary school teachers in Yogyakarta. The clustering of lipid abnormalities, elevated blood pressure, impaired glycemic control, and early renal metabolic stress reflects an emerging pattern consistent with the early stages of metabolic syndrome. This clustering is of particular concern because teachers—despite being influential community role models—are often overlooked in occupational health surveillance. Sedentary teaching schedules, prolonged sitting, and limited structured exercise opportunities likely contribute to the elevated risk profile observed in this study ([Bekel & Thupayagale-Tshweneagae, 2020](#)).

The strong association between overweight–obesity and multiple metabolic markers aligns with established pathophysiological mechanisms: chronic adipose-driven inflammation, insulin resistance, endothelial dysfunction, and dysregulated lipid metabolism. Notably, even mild elevations in creatinine, although less prevalent, showed a pronounced correlation with multi-factor metabolic clustering. This finding underscores the importance of renal function markers as early warning signals for cardiometabolic dysregulation, supporting their inclusion as key parameters in future predictive Modeling ([Fotheringham et al., 2022](#)).

Herbal supplement consumption was common among teachers but did not demonstrate measurable associations with metabolic improvements in this cross-sectional assessment. This finding suggests that herbal use may be irregular, unstandardized, or insufficient in dosage, highlighting the need for better guidance, quality assurance, and integration of evidence-based herbal interventions ([Widayati et al., 2024](#)).

The results of this study provide essential variables—BMI, cholesterol, and creatinine—as foundational components for building a predictive mathematical model of non-communicable disease (NCD) risk. Such a model would enable the early identification of high-risk individuals, facilitate targeted interventions, and support informed resource allocation in primary care. Furthermore, model-based risk stratification could be integrated into digital health platforms to improve screening efficiency in schools ([Garcia et al., 2020](#)).

The projected benefits of implementing this predictive model are substantial. First, it supports the early identification of high-risk individuals, enabling the timely initiation of lifestyle modifications, pharmacological therapy, or targeted health education. Second, the model enhances precision prevention, allowing clinicians and policymakers to prioritize interventions for populations with the highest predicted risk, thereby improving the cost-effectiveness of health programs. Third, it facilitates population-level surveillance, offering insights into emerging trends in metabolic risk profiles and helping to forecast future burdens of NCDs. Fourth, the model can be embedded into digital health platforms, wearable devices, or electronic medical records to support continuous monitoring and personalized feedback ([Pervanidou et al., 2023](#)). Ultimately, the development of a mathematical prediction model strengthens health-system resilience and contributes to long-term NCD control strategies. By transforming routine clinical and lifestyle data into actionable predictive insights, the model empowers clinicians, health administrators, and communities to shift from reactive treatment of advanced disease

toward proactive prevention—an imperative step for reducing morbidity, mortality, and economic losses associated with NCDs (He et al., 2025; Leisegang et al., 2021).

Future work should involve validating the model using longitudinal datasets, refining risk weights through regression calibration, and incorporating behavioral factors such as physical activity, dietary patterns, and sleep quality to enhance predictive accuracy. Overall, this study highlights the urgent need for biomathematical approaches in addressing NCD prevention in high-risk occupational groups (Muharram et al., 2024).

5. Conclusion

The prevalence of overweight and obesity among private elementary school teachers in Yogyakarta was found to be 47%. The data indicate that a significant proportion of these teachers exhibit risk factors for non-communicable diseases (NCDs), including overweight, hypercholesterolemia, and hypercreatininemia. Several individuals also showed signs of metabolic or renal disturbances that warrant clinical attention. Furthermore, the use of herbal medicine has not yet become a widespread practice among private elementary school teachers, as indicated by the low proportion of reported users (19.7%).

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