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META-REGRESSION OF SOCIOECONOMIC FACTORS AND THE PREVALENCE OF PHYSICAL DISORDERS IN HYPERTENSIVE PATIENTS

Nur Silviyah Rahmi [1*], Suci Astutik [2], Ni Wayan Surya Wardhani [3], Adinda Gita Maharani [4], Atmadani Rahayu Fakhrunnisa [5], Husnul Khatimah [6], Silvia Intan Aulia [7]

[1,2,3,4,5,6,7]*Department of Statistics, Faculty of Mathematics & Natural Sciences, Universitas Brawijaya*
Jl. Veteran Ketawanggede, Lowokwaru, Malang, 65145, Indonesia

*Corresponding author's e-mail: * **silviyahrahmi@ub.ac.id***

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ABSTRACT

Hypertension is a common degenerative disease with a high mortality rate and a significant impact on quality of life and productivity. Education level plays a crucial role in understanding and managing hypertension, where higher education levels can contribute to reducing the risk of hypertension. This study utilized meta-analysis and meta-regression to explore the relationship between education level and hypertension prevalence. Secondary data from eight previous studies conducted between 2015 and 2023 were analyzed. Heterogeneity analysis was performed to determine the appropriate meta-analysis model, with a random-effect model selected based on the test results. Of the eight studies analyzed, five showed a negative odds ratio, indicating that individuals with higher education levels have a lower likelihood of developing hypertension compared to those with lower education levels. The heterogeneity test showed significant variability among the studies (I2 = 91.38%). The random-effect model estimated a combined effect size with an ln odds ratio of -0.1777 and a 95% confidence interval of -0.3228 to -0.0326. These findings suggest that higher education levels are associated with a lower risk of hypertension. This underscores the importance of improving access to quality education as part of public health strategies to reduce the incidence of hypertension and enhance overall community well-being.

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1. INTRODUCTION

Hypertension is one of the degenerative diseases that are frequently encountered, with a relatively high mortality rate and a significant impact on a person's quality of life and productivity. Hypertension, or high blood pressure, occurs when blood pressure increases abnormally and continuously, exceeding 140 mmHg for systolic and 90 mmHg for diastolic on two separate measurements taken five minutes apart in a state of adequate rest or calm. If not detected and treated early, hypertension can lead to serious conditions such as kidney failure, coronary heart disease, and stroke [1].

According to [2], the prevalence of hypertension in Indonesia reached 34.1%, showing a significant increase compared to 2013, which was 25.8%. This reflects a serious health risk in the community, with only one-third of hypertension cases being diagnosed. Meanwhile, [3] reported that the number of people with hypertension worldwide reached 1.13 billion and is projected to increase to 1.5 billion by 2025, with 10.44 million deaths annually due to high blood pressure.

In general, hypertension is often called the "silent killer" because it often shows no specific symptoms until serious damage occurs to vital organs. Some symptoms that may be experienced by people with hypertension include severe headaches, fatigue or confusion, vision problems, chest pain, difficulty breathing, irregular heartbeats, blood in urine, and a pulsating sensation in the chest, neck, or ears.

According to [4], factors influencing the occurrence of hypertension include age, sex, Body Mass Index (BMI), psychological condition, and physical an activity. Additionally, hypertension can also be influenced by socioeconomic factors, one of which is the level of education.

Education level plays an important role in the understanding and management of hypertension. Better knowledge of healthy lifestyle and health management, which is generally acquired through higher education, can contribute to lowering the risk of developing hypertension. A good education allows individuals to understand the importance of a healthy diet, such as reducing the consumption of salt and saturated fats, and encouraging regular physical activity. In addition, individuals with higher levels of education tend to have a higher awareness of the dangers of risky habits, such as smoking and excessive alcohol consumption, and are therefore better able to avoid them.

Furthermore, higher education is also associated with better access to health services, in terms of information, facilities and economic means. This allows individuals to perform early detection and treatment of hypertension more effectively, thereby minimizing the potential for complications. Thus, education level can be considered as one of the major social determinants of health, particularly in the context of hypertension prevention and control. Public health interventions that consider educational factors have the potential to produce a more optimal impact in reducing the prevalence of hypertension and improving the overall quality of life of the community.

In the context of research, meta-regression can be used to explore the relationship between socioeconomic factors, such as the level of education, and hypertension. According to [5], meta-regression is an extension of meta-analysis that allows for the investigation of the extent to which heterogeneity among the results of several studies can be associated with one or more characteristics of those studies. This method is used to explain heterogeneity by associating the effect size with one or more common characteristics of the studies so that differences between studies can be understood. As in multiple regression analysis, meta-regression has one dependent variable and a set of independent variables, with the unit of analysis being the study. Heterogeneity in meta-analysis can be identified through a random-effects model, where covariates are used to identify significant covariates related to the studies.

The use of meta-regression allows researchers to identify and understand how socioeconomic factors, such as education level, influence the prevalence and management of hypertension. Through this approach, it is possible to analyze whether and to what extent socioeconomic variables contribute to differences in results between studies. Understanding the influence of these factors is crucial in designing more effective intervention strategies, both in terms of prevention and management of hypertension. By considering socioeconomic variables such as education, intervention programs can be tailored in a more targeted manner to reach higher risk groups. The ultimate goal is to reduce the incidence of hypertension and improve the overall quality of life through an evidence-based approach orientated towards the social determinants of health.

2. RESEARCH METHODS

2.1. Data

The data used in this study consist of secondary data sourced from eight previous studies conducted between 2015 and 2023. Data collection was performed by searching for related topics in journals on PubMed and Google Scholar. Studies that matched the topic were then recorded for use in the analysis process.

2.2. Effect Size

Effect size is a value which reflects the magnitude of the treatment effect or in general the strength of the relationship between two variables [5]. Effect size can also be considered a measure of the meaningfulness of research results in a practical setting [6]. This measure complements the analytical information provided by significance tests. Information about effect size can also be used to compare the effect of a variable from studies that use different measurement scales [7].

The eight studies used in this meta-analysis were selected based on several stringent criteria to ensure suitability and data quality. Firstly, all studies explicitly examined the relationship between variables relevant to the main focus of this research, namely the effectiveness of an intervention or the effect of a particular variable in the context of education, psychology or public health. Second, the studies provided quantitative data that allowed the calculation of effect sizes, such as means, standard deviations, or correlations. Third, only studies with comparable methodological designs including experiments, quasi-experiments, and correlational studies were included. Fourthly, these studies were from scientifically published sources and had undergone a peer review process, which ensures the validity and reliability of the findings. Finally, studies were selected from the time span between 2015 and 2023 to ensure the relevance of the data to the current context and challenges.

These studies were considered representative as they were similar in research focus, examining the effect of an intervention or the relationship between variables, which is in line with the purpose of this meta-analysis. In addition, all studies used quantitative approaches that allow for consistent calculation of effect size, such as Cohen's d or Pearson correlation. Conformity in methodological design, such as the use of control groups, validated measurement instruments and similar statistical analysis techniques, reinforced the homogeneity of the analyzed data.

Table 1. Nomenclature for 2 × 2 Table of Outcome by Treatment

	Events	Non-Events	N
Treated	A	B	n_1
Control	C	D	n_2

The terms effect sizes are used in different ways by different people. Meta-analyses in medicine often refer to the effect size as treatment effect, and this term is sometimes assumed to refer to odds ratios, risk ratios, or risk differences, which are common in meta-analyses that deal with medical interventions [5]. The kind of medical data used is basically based on a binary outcome such as events and non-events in two groups (the classic 2×2 table). The following is a table of binary data with (2×2) order used in the calculation of effect size. From **Table 1**, the risk ratio, odds ratio, and risk difference can be calculated.

2.2.1. Risk Ratio (RR)

Risk ratio is a comparison between two risks, which is a comparison of the probability of occurrence of an event between the case group and the control group. This ratio is used to measure the magnitude of the association between an exposure and an outcome, such as a disease or health condition.

In general, the risk ratio is calculated by comparing the risk of events in the exposed group with the risk of events in the unexposed group. If the risk ratio value is > 1, then there is an increased risk in the exposed group; if < 1, then the exposure may be protective; and if $= 1$, then there is no difference in risk between the two groups.

$$RR = \frac{A/n_1}{C/n_2} \tag{1}$$

2.2.2. Odds Ratio (OR)

Odds ratio (OR) is the ratio between two odds, which describes the comparison of the likelihood of an event between the case group and the control group. In the context of epidemiology and health research, odds ratio is often used to measure the strength of association between an exposure and a particular outcome.

Odds ratio has statistical properties that make it the preferred choice in many meta-analyses, especially when the available data are from case-control studies or when the incidence of events is low. In situations where the risk of an event is low, the odds ratio value will be close to the risk ratio value, making the interpretation similar. The computational formula for the odds ratio based on **Table 1** is as follows.

$$OR = \frac{AD}{BC} \tag{2}$$

2.2.3. Risk Difference (RD)

Risk difference is the difference between two risks, which is the difference between the probability of an event occurring in the exposed and unexposed groups. Unlike the risk ratio and odds ratio, which are relative, the risk difference provides an absolute measure of the effect of exposure. Risk difference indicates how much the risk increases or decreases directly due to a particular exposure. The risk difference value can be positive (if the risk is higher in the exposed group), negative (if the risk is lower in the unexposed group), or zero (if there is no difference in risk between the two groups). Unlike risk ratio and odds ratio calculations which are often done in logarithmic units, risk difference calculations are done in raw units. This means that the results directly reflect the difference in proportions without the need for log transformation. The computational formula for the risk difference based on **Table 1** is as follows.

$$RD = \left(\frac{A}{n_1}\right) - \left(\frac{C}{n_2}\right) \tag{3}$$

2.3. Meta-Analysis

Meta-analysis is a quantitative, formal, epidemiological study design used to systematically assess the result of previous research to derive conclusions about that body of research. Meta-analysis simply is a research method carried out by summarizing, reviewing, and analyzing research data from several pre-existing studies. The primary goal of meta-analysis is to summarize the findings of studies on the same topic to derive a conclusion in the form of an effect size. The study is based on randomized, controlled clinical trials. Most meta-analyses are based on one of two statistical models, the fixed-effect model or the random-effect model.

2.3.1. Heterogeneity Test

Heterogeneity is the difference in characteristics present in multiple studies. The problem of heterogeneity in meta-analysis arises when heterogeneity exceeds the sampling variation in the study, which if ignored will cause an under estimate of the parameters. Hypothesis testing in heterogeneity testing is as follows.

$H_0 : \tau^2 = 0 \; (\theta_1 = \theta_2 = \ldots = \theta_8 = \theta)$
$H_1 : \tau^2 \neq 0$ (there is at least one $\theta_i \neq \theta \, , i = 1, 2, \ldots, 8$)

If the $p-value$ from the results of hypothesis testing > 0.05 then the merger is carried out with the fixed-effect meta-analysis model. Conversely, if the results of hypothesis testing show a $p-value \leq 0.05$ then the merging model is carried out with a random-effects meta-analysis model **[8]**.

2.3.2. Random-Effect Modeling Meta-Analysis

Heterogeneity which has a significant effect, makes the random-effects meta-analysis model chosen. The random-effects meta-analysis model assumes that the true effect could vary from study to study due to the differences (heterogeneity) among studies. The random-effects meta-analysis model is formulated as follows **[9]**.

$$y_i = \theta + v_i + \epsilon_i \tag{4}$$

where:

y_i : value of the effect size for the i-th observation
θ : population mean effect size
v_i : random-effect for the i-th observation, $v_i \sim N(0, \sigma^2)$
ϵ_i : error of the i-th observation, $\epsilon_i \sim N(0, \sigma^2)$

To estimate the parameter θ, the Weighted Least Square (WLS) method can be used.

$$\theta = \frac{(\sum_{i=1}^{k} w_i y_i)}{\sum_{i=1}^{k} w_i} \tag{5}$$

where:

$$w_i = \frac{1}{\sigma_i{}^2} \tag{6}$$

The random-effects meta-analysis model is not only used to estimate the combined effect size in the population, but also used to estimate the variance between studies caused by variability (τ^2: tau-squared) in the population effect size. One method to estimate τ^2 and assess heterogeneity among studies is through the following equation.

$$\tau^2 = \frac{Q - df}{C} \tag{7}$$

where:

Q : heterogeneity among observations

where:

$$Q = \sum_{i=1}^{k} w_i y_i{}^2 - \frac{(\sum_{i=1}^{k} w_i y_i)^2}{\sum_{i=1}^{k} w_i} \tag{8}$$

$$df = k - 1 \tag{9}$$

$$C = \sum_{i=1}^{k} w_i - \frac{\sum_{i=1}^{k} w_i{}^2}{\sum_{i=1}^{k} w_i} \tag{10}$$

To assess the proportion of variance among studies that reflects true differences in effect sizes, the following equation can be used.

$$I^2 = \left(\frac{Q - df}{Q}\right) \times 100\% \tag{11}$$

where:

I^2 : the proportion of total variance in effect size

The scale of I^2 ranges from 0% to 100%. Several benchmarks for I^2 are commonly used is 25% that indicates low heterogeneity, 50% that indicates moderate heterogeneity, and 75% that indicates high heterogeneity [5].

2.4. Meta-Regression

Meta-regression is a development of meta-analysis that is used to determine the extent of heterogeneity or differences in results among the various studies analysed. Meta-regression is performed on pooled data obtained from several studies, with the aim of evaluating the effect of one or more categories (variables) on the observed results. In addition to measuring heterogeneity, meta-regression can also be used to identify covariates or factors that contribute to variation in outcomes between studies. Thus, it can be known which covariates have the most influence in the analysed studies.

Testing for heterogeneity in meta-regression is done by including covariates into the model, so that the contribution of each covariate to the variation between studies can be evaluated. Parameter estimation in meta-regression can be done using a fixed-effects model, which can then be followed by a random-effects model to capture variation that cannot be explained by the covariates included [10].

2.4.1. Fixed-Effect Modeling Meta-Regression

A fixed-effects meta-regression model is one that incorporates covariates into the meta-analysis and assumes that there is no between-study variance (between individual study effects). That is, all studies analyzed are considered to be from the same population and have identical true effects. In other words, this model assumes that all differences between study results are solely due to sampling error and not due to differences in the underlying study or population characteristics. In this model, covariates are used to explain variations in effect size between studies. However, as the fixed-effects model assumes no true heterogeneity between studies, the results and their interpretation are only valid for the studies analyzed, not for generalization to the wider population. The fixed-effects meta-regression model can be expressed as follows.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_m x_{im} + \varepsilon_i \tag{12}$$

where:

y_i : effect size of the i-th observation
β_0 : constant value
β_m : regression coefficient values (where m represents the number of covariates)
x_{im} : value of covariate m in the i-th observation
ε_i : error of the i-th observation, $\epsilon_i \sim N(0, {\sigma_i}^2)$

Parameter testing involving more than one covariate is done through simultaneous tests and partial tests. The simultaneous test is used to determine whether all covariates together (simultaneously) have a significant influence on the effect size in the meta-regression model. In other words, the simultaneous test aims to test the existence of an overall relationship between all covariates included in the model and the dependent variable, so that it can be known whether the model as a whole has a good fit in explaining variations in effect size between studies. After the simultaneous test is conducted, the partial test can be used to evaluate the effect of each covariate individually, to determine which covariates significantly contribute to the model [11].

2.4.2. Random-Effect Modeling Meta-Regression

The random-effects meta-regression model is one approach used to evaluate the influence of covariates on effect size in meta-analysis. This model extends the conventional meta-analysis framework by including covariates to explain variation or heterogeneity between the results of the studies analyzed. Unlike the fixed-effects model which assumes that all studies have the same effect and that differences between studies are only due to sampling error, the random-effects model accommodates the possibility that each study has a different true effect. Therefore, this model is more realistic when there is significant heterogeneity between studies.

This model allows for parameter estimation and inferential statistical calculations based on a combination of fixed effects and random effects. In the context of meta-regression, fixed effects refer to the contribution of covariates to effect size, while random effects represent the natural variation between studies that cannot be fully explained by covariates. One important component of this model is the estimation of the between-study variance, denoted by τ^2 (tau-square). The value of τ^2 indicates the amount of heterogeneity that is not explained by the covariates. To estimate τ^2, the method of moments is used, which is a statistical technique that matches the empirical variance (observations) with the theoretical variance (expectations) based on the model. The estimation of τ^2 is done iteratively, which means that the calculation process is done repeatedly until a stable or convergent value of τ^2 is obtained. This iterative process is important because the initial value of τ^2 can affect the final result, and it needs to be adjusted gradually to make the parameter estimation more accurate [11]. The meta-regression model with more than one covariate can be expressed as follows.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_m x_{im} + v_i + \varepsilon_i \tag{13}$$

where $v_i \sim N(0, \tau^2)$ dan $\varepsilon_i \sim N(0, {\sigma_i}^2)$
y_i = effect size of the i-th observation
β_0 = constant value

β_m = regression coefficient values (where m represents the number of covariates)
x_{im} = value of covariate m in the i-th observation
ε_i = error of the i-th observation, $\epsilon_i \sim N(0, {\sigma_i}^2)$

2.4.3. Mixed-Effect Modeling Meta-Regression

The mixed-effects model in meta-regression has a model denoted by $W_{tk}'Y_k$ and can be used to obtain variability between trials. Mixed-effects meta-regression model can also be used to reflect the treatment effects present in the study. The predictor variables present in the observations are considered as sources of variance in the response variable [12].

2.5. Research Variables

The variables in this study are divided into two categories, namely the outcome variable (Y) and the explanatory variables or covariates (X) related to effect size. The units studied in this case are research studies that have been conducted and published. The explanation for each variable is as follows.

1. The outcome variable is the prevalence of hypertensive and non-hypertensive patients in each study (Y).

   The prevalence of hypertensive and non-hypertensive patients is influenced by several factors, such as socioeconomic factors and physical conditions. One of the socioeconomic factors is the level of education of the patients, which determines their breadth of knowledge. Meanwhile, a physical condition or disorders can be indicated by Body Mass Index (BMI). A high BMI can lead to hypertension.

   Body Mass Index (BMI) was used as the only covariate in this study because it has a direct and strong relationship with blood pressure, and is the most commonly used physiological indicator to assess hypertension risk. BMI is also easy to measure objectively and consistent across different populations, making it a practical and valid choice as the main physiological covariate in this analysis. Meanwhile, although socioeconomic factors such as income and type of employment also have the potential to influence the prevalence of hypertension, these variables tend to have an indirect influence on hypertension through lifestyle or access to health services, which are already partially reflected in the education and BMI variables. Therefore, to maintain consistency of analysis and avoid bias due to incomplete or heterogeneous data, only BMI was included as a covariate in the analysis model.

2. Level of Education (X_1)

   The first explanatory variable or covariates in this study is the level of education of hypertensive and non-hypertensive patients. Levels in education refer to the different educational opportunities and pathways available to individuals. These typically correspond to the number of years a person spends in formal schooling. The levels of education that are used in this study was stratified into 2 groups: basic education and higher education level. The basic education level includes no education, primary education (kindergarten and elementary school), and secondary education (junior high school and senior high school). The higher education level refers to the level of education that follows the completion of secondary education, typically provided by universities, colleges, and other institutions offering degrees, diplomas, and certificates. It includes associate, bachelor's, master's, and doctoral degrees. Education is important in advancing the quality of a country's human resources because education itself is a series of processes of changing behavior, increasing knowledge, and life experience so that a person's mind and characteristics can mature [13].

   Level of education is considered less education or insufficient when both hypertensive and non-hypertensive patients have only completed basic education. Conversely, the level of education is deemed sufficient when both hypertensive and non-hypertensive patients have attained higher education. This is based on the general understanding that the higher the level of education a person achieves, the broader their knowledge about health, particularly regarding the risks of hypertension. This increased awareness leads to a greater concern for their health.

3. Body Mass Index (BMI) (X_2)

The second explanatory variable or covariates in this study is the Body Mass Index of hypertensive and non-hypertensive patients. The Body Mass Index or BMI was used to assess the degree of obesity in patients. The BMI was calculated as measured body weight in kilogram (kg) divided by the square of height in meters. Patients were stratified into the following groups based on BMI: underweight (BMI < 18.5 kg/m^2), normal weight (BMI between 18.5 and 22.9 kg/m^2), overweight (BMI between 23 and 24.9 kg/m^2), and obese (BMI ≥ 25 kg/m^2). However, the BMI data used in this study is the average number of patients categorized as normal weight and overweight across each study.

3. RESULTS AND DISCUSSION

3.1 Meta-Analysis on Level of Education

Before conducting meta-analysis modeling on level of education, first determine the effect size. Effect size is determined based on information from previous studies used. Previous studies used the odds ratio as the result of interpretation, so the effect size used is the odds ratio.

Table 2. Effect Size of Level of Education Variable

Researcher	Ln Odds Ratio	Var Ln Odds Ratio
Hodimatum Mahiroh, et al. (2019) [14]	-0.2126	0.0016
Masuma Akter Khanam, et al. (2015) [15]	0.0783	0.0209
Selly Ruth Defianna, et al. (2021) [16]	-0.2833	0.0018
Diah Adelia Emilda, et al. (2023) [17]	-0.2597	0.0083
Chan Soon Park, et al. (2016) [18]	-0.1828	0.0022
Shikha Singh, et al. (2017) [19]	0.0394	0.0236
Irene R. Degano, et al. (2017) [20]	-0.5165	0.0021
Muhammad Abdul Baker Chowdhury, et al. (2016) [21]	0.0918	0.0062

Table 2 shows that there are 5 studies that have negative natural logarithm of odds ratio (ln odds ratio). This indicates that in these five studies, the odds of having hypertension were higher in individuals with sufficient education compared to those with lower education levels.

In other words, the results of the five studies show an association that contradicts the general assumption that higher education always has a protective effect on hypertension risk. This finding may reflect the presence of confounding factors or differences in the social, economic and cultural context of each study that influence the relationship between education and hypertension.

3.1.1 Heterogeneity Testing

Heterogeneity testing uses the following test hypothesis. Heterogeneity testing uses the following test hypothesis.

$H_o: \tau^2 = 0$ ($\theta_1 = \theta_2 = \dots = \theta_8 = \theta$) (Between studies are homogeneous)
$H_1: \tau^2 \neq 0$ (there is at least one $\theta_i \neq \theta, i = 1,2,\dots,8$) (Between studies are heterogeneous)

Table 3. Heterogeneity Testing

Q (df = 7)	$p - value$
64.8770	<0.001

Based on the Table 3 of heterogeneity testing, the Q value using the Restricted Maximum Likelihood (REML) estimator is 64.8770. At the 5% significance level, $X^2_{(7:0.05)}$ is obtained 14.067. This means that the value of Q (64.8770) is greater than $X^2_{(7:0.05)}$ (14.067) so reject H_o. The results of heterogeneity testing also show a $p - value$ of < 0.001 which means less than 0.05 so that reject H_o. Thus, it can be concluded that the effect size of the 8 studies is heterogeneous, so the random-effect model is more appropriate to use.

3.1.2 Random-Effect Modeling Meta-Analysis

In addition to estimating the population effect size, the random-effect model also estimates the variance between studies. The estimation of between-study variance and some other measures of heterogeneity are given below.

Table 4. Random-Effect Meta-Analysis Heterogeneity Measure

Heterogeneity Measure	Value	$p - value$
Q	64.8770	<0.001
τ^2	0.0369	
τ	0.1920	
I^2	91.38%	

The **Table 4** provides information on several measures of heterogeneity, variance between studies (τ^2) estimated using the Restricted Maximum Likelihood (REML) estimator of 0.0369 with a research standard deviation of (τ) is obtained 0.1920. The I^2 index showed that the level of heterogeneity in this analysis was very high, at 91.38%. This value suggests that a large proportion (91.38%) of the total observed effect size variability can be attributed to real differences between studies rather than random error alone. However, there is limited discussion on the potential sources of heterogeneity and their analytical implications. Therefore, it is recommended to conduct subgroup analyses based on study characteristics (e.g. study design, population, geographical location, or methodological quality) to identify factors that may account for such variation. In addition, sensitivity analyses can also be conducted to assess the stability of the meta-analysis results by evaluating the influence of individual studies (e.g. outlier studies or studies with a high risk of bias) on the pooled effect estimate. These approaches will provide a deeper understanding of the data structure and strengthen the reliability of result interpretation. The combined effect size estimate is given as follows.

Table 5. Estimated Combined Effect Size of Level of Education Random-Effect Model Meta-Analysis

	Estimation	Standard Error	Z_{count}	$p - value$	95% Confidence Interval
θ	-0.1777	0.0740	-2.3996	0.0164	-0.3228; -0.0326

Testing the significance of model parameters is done using the following hypothesis.

$H_o: \theta = 1$
$H_1: \theta \neq 1$

Based on the test results with a significance level of 5%, $z_{(0.025)}$ is obtained as 1.96. In the **Table 5**, it is found that $|Z_{count}|$ is $[-2.3996] = 2.3996$ which means it is greater than $z_{(0.025)}$ (1.96) so reject H_o. This means that the population mean effect size affects the observed effect size. The combined effect size estimation result is -0.1777 indicating the association between education level and hypertension risk. The value was transformed into $\exp(-0.1777) = 0.837194$, meaning that the combination of 8 studies resulted in individuals with sufficient levels of education having almost twice the chance of contracting hypertension compared to individuals with less education. The 95% confidence interval, which is from -0.3228 to -0.0326, includes no zeros, which reinforces the conclusion that there is a real effect. In a practical context, this means that an increase in education level is consistently associated with a decrease in the effect size under study. After obtaining the estimated population effect size and the estimated variance between studies, the random-effect meta-analysis model for level of education is written as follows.

$$y_i = 0.837194 + v_i + \epsilon_i \tag{14}$$

3.2 Meta-Regression on Level of Education

Based on the analysis of the random-effect model that has been conducted, it shows that there is significant heterogeneity among the 8 effect sizes. The existence of heterogeneity in effect size allows the causes to be explored and explained. Variables that are thought to explain the heterogeneity are Body Mass Index. Next, a meta-regression analysis was conducted with a random-effect model, but first conducted a fixed-effect meta-regression analysis as an initial iteration.

Table 6. Parameter Estimation of Mixed-Effect Meta-Regression Model of Level Education Variable

	Estimation	Standard Error	Z_{count}	$p-value$	95% Confidence Interval
Intercept	-0.0436	0.1412	-0.3086	0.7576	-0.3203 ; 0.2332
BMI	-0.0005	0.0004	-1.1154	0.2647	-0.0013 ; 0.0003
Model (Q_{model}) = 1.2441			df = 2	$p-value$ = 0.2647	

Testing the significance of model parameters is done using the following hypothesis.
$H_o: \beta = 0$
$H_1: \beta \neq 0$

In Table 6, the coefficient value for the BMI (Body Mass Index) variable was recorded as -0.0005 with a 95% confidence interval between -0.0013 and 0.0003. Since this interval includes zero, it can be concluded that there is statistically insufficient evidence to suggest that BMI has a significant influence on the association between education level and hypertension incidence. In other words, the role of BMI in explaining variations in the relationship between education and hypertension is not significantly proven in this model, so BMI cannot be said to be an influential moderator variable in this context.

In addition, the results of simultaneous testing were conducted to assess whether there are variables that jointly influence the effect size in the model. Based on the results of simultaneous testing with a significance level of 5%, $X^2_{(1;0.05)}$ is 5.9915. This means that the value of Q_{model} (1.2441) is less than $X^2_{(1;0.05)}$ (0.2647) so accept H_o. This means that there is no significant variable that affects the effect size.

Then a partial test is carried out with the following hypothesis.

H_o: $\beta_i = 0$
H_1: $\beta_i \neq 0$, $i = 1,2$

Based on a partial test with a significance level of 5%, the $\boldsymbol{Z}_{(0.025)}$ the value is 1.96. In the variable of BMI obtained $|\boldsymbol{Z}_{count}|$ of 1.1154, this means that the value of $|\boldsymbol{Z}_{count}|$ is less than $\boldsymbol{Z}_{(0.025)}$ (1.96) so accept H_o which means that BMI partially has no effect on the effect size. After conducting partial and simultaneous tests, proceed with testing residual heterogeneity which is given in Table 7 with the following hypothesis.

H_o: $\tau^2 = 0$ (Between studies are homogeneous)
H_1: $\tau^2 \neq 0$ (Between studies are heterogeneous)

Table 7. Testing for Unexplained Heterogeneity of Level of Education Variables

Source of Variance	Q	df	$p-value$
Residual ($Q_{residual}$)	59.4255	6	<0.0001
τ^2	0.0370		

*) significant with a 5% significance level

Using a significance level of 5%, the critical value of the chi-square distribution with 6 degrees of freedom is $X^2_{(6;0.05)}$ =12.5916. The Q residual value obtained from the analysis is 59.4255. Since the Q residual value is greater than the chi-square critical value (59.4255 > 12.5916), the null hypothesis (H_0) is rejected. This means that the variation between studies that cannot be explained by the variables included in the model (in this case, education level) is not zero. In other words, there is still significant heterogeneity in effect size between studies, and the education level variable is not sufficient to explain the differences in results found across studies.

The resulting value of τ^2 estimated amount of residual heterogeneity is 0.0370. The variance estimates between studies increased to 0.0370 from a previous meta-analysis value of 0.0369, indicating that (0.0369 - 0.0370) / 0.0369 = -0.00271 of the total heterogeneity. This result is negative, which means that the variance between studies actually increases slightly after including the education level variable in the model. This small increase indicates that the addition of the variable does not help reduce heterogeneity between studies. Thus, it can be concluded that there are most likely other factors beyond education level that influence the effect size differences in the analyzed studies.

After conducting all tests, the random-effect model can be written as follows.

$$\ln(\mathrm{OR}) = -0.0436 - (-0.0005) * \text{level of education} \tag{15}$$

Based on the results of the random-effects meta-regression model, an association was found between higher education levels and a reduced risk of hypertension. Individuals with higher educational backgrounds generally have a better understanding of health, greater access to health information, and a tendency to adopt healthy behaviors, such as a better diet, regular physical activity, and adherence to medication or health checks.

These factors may indirectly contribute to the lower prevalence of hypertension in groups with higher education. This finding indicates that education level can be an important indicator in understanding the social determinants of public health, particularly in the prevention and control of non-communicable diseases such as hypertension.

However, it is important to note that these findings are from an observational study, so the relationship shown is associative and cannot be interpreted as causality. In other words, it cannot be concluded that a higher level of education directly leads to a reduced risk of hypertension.

In addition, it is important to consider that there are other variables that may also influence the results of the analysis, such as income level, type of employment, and access to health services. These variables may serve as confounding factors that have not been fully controlled for in the model. Therefore, interpretation of the results of this study needs to be done with caution. Further analyses with more robust study designs, such as longitudinal or intervention studies, are needed to confirm a more conclusive causal relationship between education level and hypertension risk.

4. CONCLUSION

The meta-analysis conducted in this study aimed to assess the relationship between the level of education and the likelihood of developing hypertension, based on data from eight previous studies. The effect sizes were determined using the odds ratio from these studies. The heterogeneity test revealed significant variability among the studies, indicating that a random-effect model was appropriate. The estimated combined effect size was -0.1777, with a significant Z-value and a confidence interval of -0.3228 to -0.0326. This suggests that individuals with higher education levels have a lower likelihood of developing hypertension compared to those with lower education levels.

AUTHOR CONTRIBUTIONS

Nur Silviyah Rahmi: Formal analysis, Funding acquisition, Writing - Review and Editing; Suci Astutik: Investigation, Resources, Validation, Writing - Review and Editing; Ni Wayan Surya Wardhani: Methodology, Visualization, Writing - review and editing. Adinda Gita Maharani: Software, Data curation, Writing - Original draft. Atmadani Rahayu Fakhrunnisa: Investigation, Project administration, Writing - Original draft. Husnul Khatimah: Investigation, Resources, Validation. Silvia Intan Aulia: Resources, Writing - Original draft. All authors discussed the results and contributed to the final manuscript.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest to report study.

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