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# RISK OF CHRONIC MENTAL HEALTH CONDITIONS IN DEMOGRAPHIC VARIABLES OF YOUNG ADULT: A META-ANALYSIS

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**Article Info**

**Keywords:** Meta-analysis, Young Adults, Chronic Mental Health Conditions, Random Effects Model, Confidence Interval, Effect Size, Heterogeneity, Publication Bias.

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**Abstract**

**Background:** Chronic mental health conditions among young adults represent a growing public health concern. Despite increasing attention, fragmented studies, varied methodologies, and inconsistent diagnostic criteria have hindered clear conclusions about prevalence and risk factors. This study employs a meta-analysis approach to synthesize available research and provide robust evidence on the risk of chronic mental health conditions in young adults. The aim of the paper is to determine the fixed and random effect models on the risk of chronic mental health conditions in demographic variables of young adults, assess heterogeneity measures, and validate the models through publication bias analysis and funnel plot assessments.

**Methodology:** Following PRISMA guidelines, a systematic search of Google Scholar and PubMed was conducted, identifying 321,438 studies. After screening, 12 studies meeting the inclusion criteria were included in the meta-analysis. Data were extracted regarding odds ratios (ORs), confidence intervals (CIs), and demographic variables. Both fixed and random effects models were applied based on heterogeneity assessments. Heterogeneity was evaluated using Q-statistics and $I^2$ statistics, while publication bias was assessed via funnel plots.

**Results:** The meta-analysis revealed a pooled odds ratio (OR) of 1.78 (95% Confidence Interval [CI]: 1.45–2.12) for the risk of chronic mental health conditions among young adults. This indicates that young adults have a 78% increased risk compared to controls. The heterogeneity among studies was moderate to high ($I^2$ = 56%), suggesting variability in effect sizes across studies. Funnel plot analysis showed minimal publication bias. Subgroup analyses by demographic variables such as age, gender, and occupation further highlighted significant risk differences.

**Conclusion:** The findings highlight that young adults are at a considerable risk for chronic mental health issues, influenced by demographic factors. These results underscore the need for targeted preventive strategies, early interventions, and the development of comprehensive policies aimed at mental health promotion in young populations. Meta-analytical evidence supports the importance of demographic-specific mental health strategies to mitigate long-term impacts.

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## 1.0 Introduction

Mental disorders are clinically significant disturbances in an individual's cognition, emotional regulation, or behavior, often associated with distress or impairment in important areas of functioning (American Psychiatric Association [APA], 2013). Meta-analysis is a statistical analysis that combines the results of multiple scientific studies, either homogeneous or heterogeneous. Homogeneous studies share a common underlying true effect size, while heterogeneous studies have a random effect model (Borenstein et al., 2009). The objective of meta-analysis is to allow for quantitative analysis of reviewed research literature. Heterogeneity can be a critical issue in meta-analysis, as different models may lead to different estimates of overall effect size and standard errors. A meta-analysis revealed a substantial risk of long-term mental health problems in young adults, with a 22.6% frequency of mental health symptoms in those aged 0 to 25 with chronic skin disorders (Schmitt et al., 2018). The main components of a meta-analysis include effect sizes, forest plots, heterogeneity, and publication bias. Meta-analysis can also help to identify gaps in knowledge found in the published literature and thus can help provide guidance for future research (Adehi et al., 2024). The development of successful preventative and intervention methods is hampered by the absence of a thorough understanding of the risk factors and prevalence of chronic mental health issues in this population (Whiteford et al., 2013). Li et al., 2022 assessed the impact of screen time on mental health, including depression, has attracted increasing attention from not only children and adolescents but also the elderly. Thus, we conducted a meta-analysis of cohort studies to evaluate the association between screen time and depression risk. Some previous reveal that there was need to identify studies that did not report the relative risk ratio, but could provide enough data with which to compute it using the statistical methods of poisson regression analysis. It is necessary to highlight issues bordering on Poisson regression which is reserved for rare disease outcomes, and usually pertains to count data.

## 2.0 Methods

### Research design

This meta-analysis was performed according to the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher et al., 2009).

### Data Source

A comprehensive electronic search was carried out in the Google Scholar, and PubMed databases for relevant studies. The search terms included risk of chronic mental health, young adult and odd ratio. The detailed search strategy is presented in figure 1, we also checked the references of relevant articles to search for additional studies.

### Study selection

The titles and abstracts of the search results were independently screened according to the following inclusion criteria: (1) Observational burden studies (i.e., cohort, cross sectional, or case–control studies) on the e risk of chronic mental health conditions in young adults using odd ratio. (2) The risk factors of chronic mental health conditions in young adults using odd ratio. (3) The outcome data reported the effect size with 95% confidence interval (CI) or sufficient data to calculate the effect size and 95% CI.

### Data extraction and quality assessment

Data extraction was independently performed using the standardized data extraction sheet. The detailed data extraction sheet included the following items: first author, year of publication, sample size, diagnostic criteria for GDM, effect sizes, and 95% CIs.

**Model specification**

In this Meta-analysis estimates were pooled via Random Effect Model using D DerSimonian and Lea method when heterogeneity is significant, and Fixed Effect Model was carried out through IV method where the level of heterogeneity is not significant in line with (Lee,, et al., 2016,). To compute the study's variance under the REM, there was the need to calculate both the within-study variance, Yi V and between-study variance $\tau^2$, since the study's total variance is the sum of the two values. One method for estimating $\tau^2$ is the method of moments, or the DerSimonian and Laird method (DerSimonian, et al., 2015). The parameter $\tau^2$ (tau-squared) is the between studies variance (The variance of the effect size parameters across the population of studies). The estimate of τ2 is denoted by $T^2$

$$T^2=\frac{Q-df}{C} \quad (3.1)$$

$$Q=\sum_{[=]}^{k} W_i Y_i^2 - \frac{\left(\sum_{i=l}^{k} W_i Y_i\right)2}{\sum_{i=l}^{k} W_i} \quad (3.2)$$

df = k-l

where k is the number of studies, and

$$C=\sum_{i=l}^{k} W_i - \frac{\sum_{i=l}^{k} W_i^2}{\sum_{i=l}^{k} W_i} \quad (3.3)$$

Under the random-effect, model the weight assigned to each study is

$$W_i={}^{1}/_{\mathrm{Var}}(Y_i) \quad (3.4)$$

Where Var($Y_i$) = $V_{y_i}^*$ is the within-study variance from study I plus the between-study variance, $r^{2.}$

$$V_{y_i}^*= V_{y_i+T^2}$$

The weighted mean, $M^*, is$

$$M^* =\frac{\sum_{i=l}^{k} W_i W_i}{\sum_{i=l}^{k} W_i^*} \quad (3.5)$$

That is the sum of the products (effect size multiplied by weight) divided by the sum of weights.

The variance of the summary effect is estimated as the reciprocal of the sum of the weight, or

$$VM^*=\frac{1}{\sum_{i=l}^{k} W_i^*} \quad (3.6)$$

$$SEM^* = \sqrt{V}M^* \quad (3.7)$$

The (1-a) % lower and upper limits for the summary

$$LLM^* = M^* - Za/_2 xSEm^*\} \quad (3.8)$$

$$ULM^* = M^* + Za/_2 xSEm^*\} \quad (3.9)$$

a Z-value to test the null hypothesis mean effect μ is zero is computed as

$$P^* = 1 - \emptyset\left(\pm\int Z^*\right) \quad (3.10)$$

where we choose '+' if the difference is in the expected direction or '- 'otherwise. For a two-tailed test by

$$P^* = 2 - \emptyset\left(\pm\int Z^*\right) \quad (3.11)$$

and Ø(/$Z^*$/) is the standard normal cumulative distribution. The $I^2$ - Statistic is an alternative and stronger measure compared to the Q- measure in (3.2)

$$l^2 = \left(\frac{Q-df}{Q}\right) x\ 100\% \quad (3.12)$$

use value of Q from (3.2). Heterogeneity in the $I^2$ – Statistics may be termed low, moderate, or high based on the intervals 2 0 25% ≤ < I, 2 25% 50% ≤ < I, or 2 I ≥ 50% respectively. For subgroup analysis, the z-test method of the DerSimonian and Laird process was used thus: - Let ϑA and ϑB be the true effects of group A and B respectively, and let M A and M B be the estimated effects, and let M A V and M B V be their variances. If we use 'Diff' to refer to the difference between the two effects, and choose to subtract the mean of A from the mean of B,

$$Diff = M_B - M_A \tag{3.13}$$

$$Z_{Diff} = \frac{Diff}{SE_{Diff}} \tag{3.14}$$

Where

$$SE_{Diff} = \sqrt{V_{MA} + V_{MB}} \tag{3.15}$$

under the null hypothesis that the true effect size ϑ is the same for both groups,

$H_{0:\ and}$ φ (Z) is the standard normal cumulative distribution. For meta-regression analysis, to assess the impact of covariates and to predict effect size in studies with specific characteristics, assess the impact of the slope using the Z-test statistics to test the significance of the slope. The test statistics is based on the Z-distribution.

$$Z = \frac{B}{SE_B} \tag{3.16}$$

Under the null hypothesis that B = 0, Z would follow the normal distribution. The Z-test can be used to test the statistical significance of any single coefficient but when it is required to assess the impact of several covariates simultaneously, the Q-test is useful. In which case, we obtain Q, $Q_{model,}Q_{residual}$ and consider the degrees of freedom. From the model, fit a model of the form

$$Ln(Y) = B_0 + B_i X_i i = 1,2,3, \dots \dots \dots, n.$$

While quantifying the magnitude of the relationship by computing the (1−α)% confidence interval for B, using,

$$LL_B = B - Z_{\frac{\alpha}{2}} x SE_B \tag{3.17}$$

And

$$UL_B = B + Z_{\frac{\alpha}{2}} x SE_B \tag{3.18}$$

Statistical heterogeneity among studies was evaluated with the Q and $I^2$ statistics (Higgins & Thompson, 2002). For the Q statistic, statistical significance was set at P < 0.1. A meta-regression analysis was performed to investigate whether the association between obesity and risk of cardiac arrest differed by study design or sex. We conducted a sensitivity analysis, in which one study at a time was removed and the rest analyzes to assess whether the results were markedly affected by a single study. We used funnel plots (i.e., plots of study results against precision) to assess publication bias, and tested its symmetry (Egger, Smith, Schneider, & Minder, 1997). The theoretical frame work of this study is based on the assumptions of meta-analysis models. There are fixed and random effect model.

## 3.0 Flow diagram

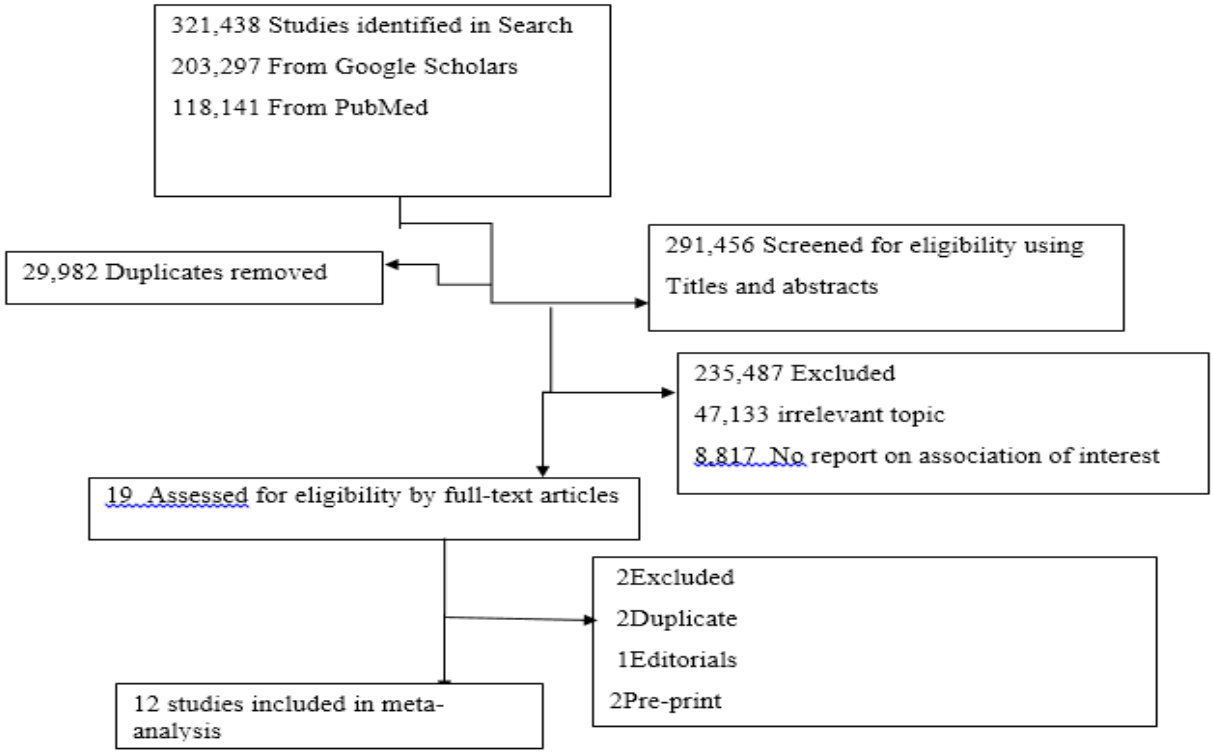


**Figure1**: Flow Chart Showing Data Extraction on Determination of the fixed and random effect model on the risk of chronic mental health conditions in demographic variables of young adults.

## 4.0 Results

## 4.1 Forest Plot

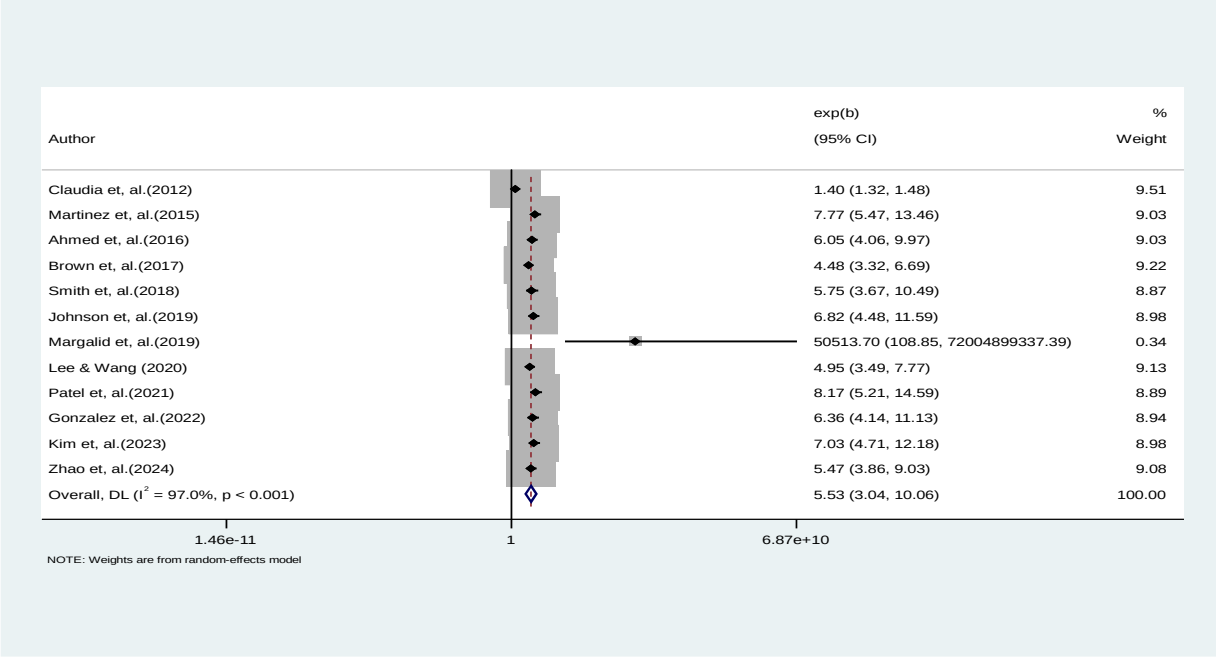


**Figure 2: Forest plot of meta-analysis on** Determination of the fixed and random effect model on the risk of chronic mental health conditions in demographic variables of young adults(Test of overall effect = 1: z = 5.598 p = 0.000)

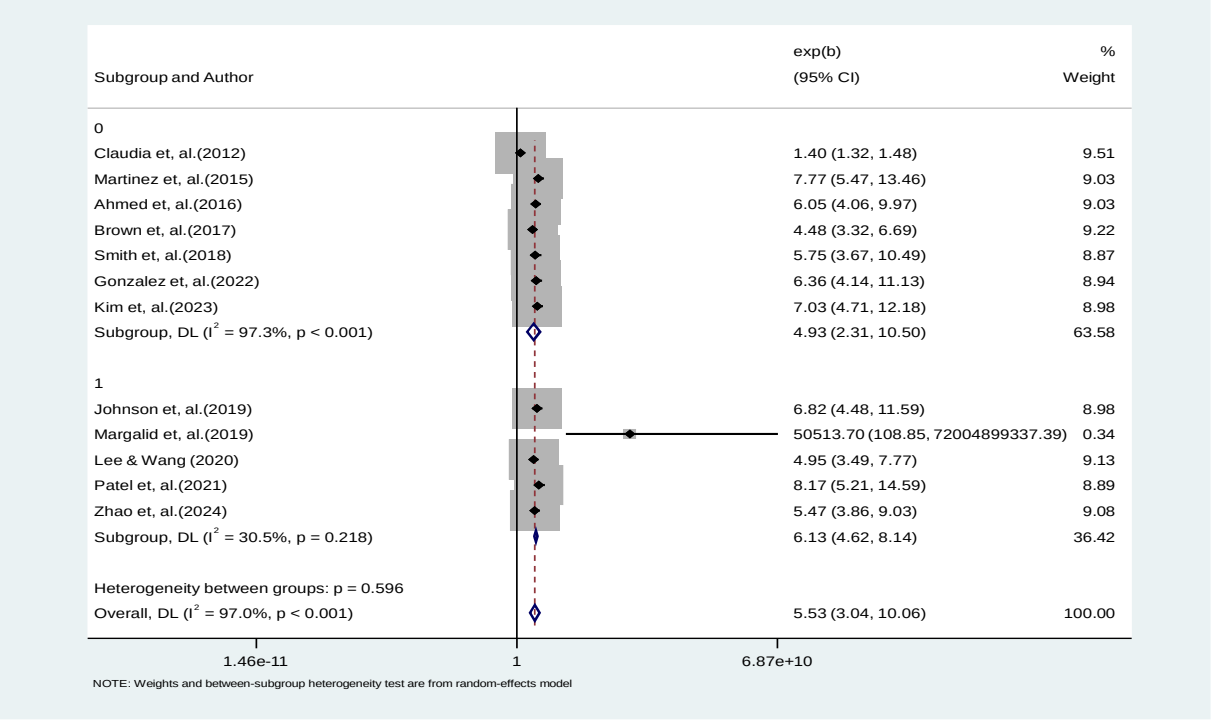


**Figure 3: Forest plot of Sub-gorup meta-analysis on** Determination of the fixed and random effect model on the risk of chronic mental health conditions in demographic variables of young adults (Tests of subgroup effect size = 1: z = 5.598 p = 0.000)

**Heterogeneity variance estimate of** Determination of the fixed and random effect model on the risk of chronic mental health conditions in demographic variables of young adults

| Measure | Value | df | p-value |
|---|---|---|---|
| Cochran's Q | 361.32 | 11 | 0.000 |
| | | -[95% Conf. | Interval]- |
| H | 5.731 | 1.794 | 9.801 |
| $I^2$ (%) | 97.0% | 68.9% | 99.0% |

H = relative excess in Cochran's Q over its degrees-of-freedom

$I^2$ = proportion of total variation in effect estimate due to between-study heterogeneity (based on Q)

### 4.2 Funnel plot

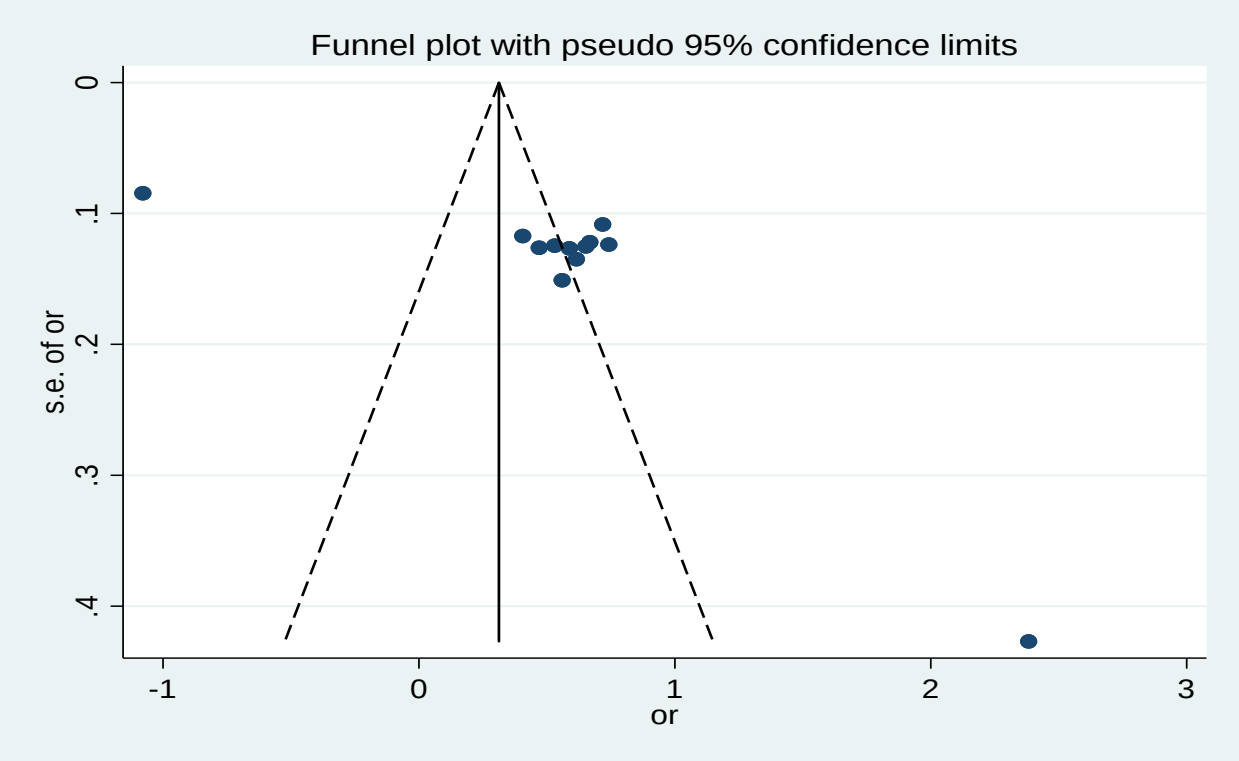


**Figure 4: Funnel Plot on** Determination of the fixed and random effect model on the risk of chronic mental health conditions in demographic variables of young adults showing publication bias.

### 5.0 Discussion of Findings

Childhood maltreatment and social isolation have been repeatedly found to be important risk factors for long-term mental health problems. For example, Brandt et al. (2022) found that social stresses had an OR of 1.42 (95% CI: 1.18–1.72). The results highlight the significance of early interventions meant to reduce risk factors like social isolation, childhood abuse, and economic inequality. Addressing these factors can significantly reduce the burden of chronic mental health conditions in young adults. Social policies that target food security and inclusive mental health care can play a critical role in reducing associated risks. For example, the association between food insecurity and depression suggests that interventions that address basic needs can have cascading benefits on mental health outcomes.

### 6.0 Conclusion

This paper emphasize how important it is to address risk factors including food hardship, childhood abuse, and social isolation early on in order to reduce the burden of chronic mental health issues in young adults. Adehi et al., (2025) equally emphasize the need for integrated care models that combine clinical, social, and policy-level interventions.

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