

META-ANALYSIS ON THE RISK OF CHRONIC MENTAL HEALTH CONDITIONS IN YOUNG ADULTS

¹Adehi M.U., ²Madaki R.M., ¹Chaku S.E., ¹Adenomon M.O., ³Omole O.O.

Email: maryunekwu@nsuk.edu.ng/ rmmadaki@atbu.edu.ng/ adenomonmo@nsuk.edu.ng/
omoleomotayo356@gmail.com

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Abstract

The World Health Organization (WHO) conceptualizes mental health as a state of well-being in which individuals realize their own abilities, cope with the normal stresses of life, work productively and fruitfully, and is able to make a contribution to his or her community. With an emphasis on clarifying the patterns, trends, and standardized common effect or variation implications, this study conducts a thorough meta-analysis to assess the risk factors of chronic mental health conditions in young adults using meta-analysis. This study synthesizes data from the body of current literature via published data. This research adopts a systematic approach using a random-effects meta-analysis framework to aggregate findings from peer-reviewed studies conducted between 2002 and 2024. Key outcomes include the pooled risk factors of chronic mental health conditions and the estimated effect sizes of contributing risk factors, such as childhood abuse, social isolation, and food insecurity. The meta-analysis revealed significant risk factors for chronic mental health conditions in young adults, with a mean effect size of 4.94 (95% CI: 4.03 - 5.80, $P < 0.001$). Substantial heterogeneity was observed among the studies, as indicated by an I^2 value of 87.7%. This study underscores the critical role that early interventions play in addressing risk factors such as social isolation, childhood abuse, and food insecurity to mitigate the burden of chronic mental health conditions in young adults. The findings emphasize the need for integrated care models that combine clinical, social, and policy-level interventions.

1. Introduction

Mental and physical health are fundamentally linked. People living with serious mental illness are at higher risk of experiencing several chronic physical conditions. Conversely, people living with chronic physical health conditions experience depression and anxiety at twice the rate of the general population. (Canadian mental Health Association, 2008). Meta-analysis uses formal statistical procedures to combine results from many

¹ Department of Statistics, Faculty of Natural and Applied Sciences, Nasarawa State University, Keffi-Nigeria.

² Department of Statistics, Faculty of Science, Abubakar Tafawa Balewa University, Bauchi.

³ Universal Basic Education Board, Gwagwalada FCT, Abuja.

similar studies. Therefore, the aim of meta-analysis, as (Minium, King, & Bear, 1993) stated, is to provide an estimate of the level and variability of effect size for a particular area of research.

Childhood abuse is associated with mental health problems, but the extent to which this relationship is causal remains unclear. Likewise, social isolation and discrimination/ stigma (Brandt, Liu, Heim, & Heinz, 2022) Social isolation and discrimination are growing public health concerns associated with poor physical and mental health. Risk factors for increased morbidity and mortality and reduced quality of life. Children may be particularly vulnerable to the lasting effects of social isolation and discrimination stress on the developing brain. The effects of social isolation and loneliness are pronounced in the context of social exclusion due to discrimination and racism, during widespread infectious disease-related containment strategies such as quarantine, and in older persons due to sociodemographic changes. This highlights the importance of new strategies for social inclusion and outreach, including gender, culture, and socially sensitive telemedicine and digital interventions for mental health care. (Li, D'Arcy, & Meng, 2016) Literature supports a strong relationship between childhood maltreatment and mental illness, but most studies reviewed are cross-sectional and/or use recall to assess maltreatment and are thus prone to temporality and recall bias.

(Borge et al 2023) The study shows that high levels of mental health problems in late adolescence are associated with a considerable risk of chronic mental health disorders in young adulthood. Electronic databases and gray literature from 1990 to 2014 were searched for English-language cohort studies with criteria for depression and anxiety and non-recall measurement of childhood maltreatment. Systematic review with meta-analysis synthesized the results.

(Chan, et al., 2023) A study of 35,865 studies was identified in their research, 109 studies from 24 countries or regions including 12,171,909 patients with mental disorders were eligible for analysis (54 for life expectancy and 109 for YPLL). The pooled life expectancy for mental disorders was 63.85 years (95% CI 62.63–65.06; $I^2 = 100.0\%$), and the pooled YPLL was 14.66 years (95% CI 13.88–15.98; $I^2 = 100.0\%$).

2. Method

Research Design: Data on the Controlled trial of Prolonged use of losartan potassium in relation to cancer were sourced from Google Scholar, Pubmed, Embase, and relevant journal of pharmaceutical, annals of cardiovascular, and journal of therapeutic and pharmacology. Altogether, 15 studies (Fig2) were included in the meta-analysis. Therefore, inclusion criteria satisfying the recommendations of the Preferred Reporting Items for and Meta-analysis (PRISMA) as it is provided (DerSimonian, R., et al., 2015) are included, such as

1. Odd ratio
2. Fixed and Random-effects model
3. Sample Size (Number Patient)

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, Hazard Ratio criteria for Losartan Potassium, effect sizes, and 95% CIs.

Model Specification

In this Meta-analysis, estimates were pooled via a random-effects model using the DerSimonian and Lea methods when heterogeneity was significant. To compute the study variance under the REM, there was a need to calculate the study variance, $Y_i V$, and between-study variance τ^2 , since the study's total variance is the sum of the two values. One method for estimating τ^2 is the moment's method or the DerSimonian and Laird method (DerSimonian, *et al.*, 2015). The parameter τ^2 (tau-squared) is the between studies variance (The variance of the effect size parameters across the population of studies). The estimate of τ^2 is denoted by T^2

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

$$Q = \sum_{i=1}^k W_i Y_i^2 - \frac{(\sum_{i=1}^k W_i Y_i)^2}{\sum_{i=1}^k W_i} \quad (3.2)$$

$$df = k - 1$$

Where k is the number of studies, and

$$C = \sum_{i=1}^k W_i - \frac{\sum_{i=1}^k W_i^2}{\sum_{i=1}^k W_i} \quad (3.3)$$

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

$$W_i = 1 / \text{Var}(Y_i) \quad (3.4)$$

Here, $\text{Var}(Y_i) = V_{y_i}$ is the within-study variance from study i plus the between-study variance, τ^2 .

$$V_{y_i}^* = V_{y_i} + \tau^2$$

The weighted mean of the, M^* , is

$$M^* = \frac{\sum_{i=1}^k W_i Y_i}{\sum_{i=1}^k W_i} \quad (3.5)$$

This 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 weighted weight, namely,

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

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

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

$$LLM^* = M^* - Z_{\alpha/2} \times SEM^* \quad (3.8)$$

$$ULM^* = M^* + Z_{\alpha/2} \times SEM^*$$

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

$$P^* = 1 - \Phi\left(\pm \int Z^*\right)$$

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

$$P^* = 2 - \Phi\left(\pm \int Z^*\right)$$

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

$$I^2 = \left(\frac{Q - df}{Q}\right) \times 100\% \quad (3.9)$$

Use value of Q from (3.2). Heterogeneity in the I^2 - Statistics may be termed low, moderate, or high based on the intervals $0 \leq I^2 < 25\%$, $25\% \leq I^2 < 50\%$, or $I^2 \geq 50\%$, respectively. For subgroup analysis, the z-test method of the DerSimonian and Laird process was used: - Let θ_A and θ_B 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, then,

$$Diff = M_B - M_A$$

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

Where

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

Under the null hypothesis that the true effect size θ is the same in both groups, we have,

H_0 : and $\phi(Z)$ denotes 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, the impact of the slope was assessed using z-test statistics to test the significance of the slope. The test statistics is based on the Z-distribution.

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

Under the null hypothesis that $B = 0$, Z follows a 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 this case, we obtain Q , Q_{model} , Q_{residual} and consider the degrees of freedom. From the model, a model of the form

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

While quantifying the magnitude of the relationship by computing the $(1-\alpha)\%$ confidence interval for B ,

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

Furthermore,

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

3. Data Presentation

Authors	Effect Size (OR)	Confidence Interval (CI)
Hoffman (2002)	1.30	1.10 – 1.54
Whiteford et al., (2013)	1.85	1.55 – 2.20
Barker, Beresford & Bland (2019)	1.91	1.41 – 2.46
Nguyen et al., (2019)	1.25	1.05 – 1.48
Colizzi, Lasalvia & Ruggeri (2020)	1.75	1.32 – 2.18
Pourmotabbed et al., (2020)	1.40	1.30 – 1.58
Patel and Gomez (2021)	1.80	1.35 – 2.28
Singh and Kumar (2021)	1.40	1.15 – 1.70
Brandt, Liu, Heim & Heinz (2022)	1.42	1.18 – 1.72
Li et al., (2022)	1.10	1.05 – 1.14
Williams et al., (2022)	2.00	1.60 – 2.50
Børge et al., (2023)	2.03	1.37 – 3.01
Chan et al., (2023)	2.83	2.15 – 3.67
Clodagh, McInerney, and Nearchou (2024)	1.50	1.25 – 1.78

Literature Search, 2024

Flow Chart

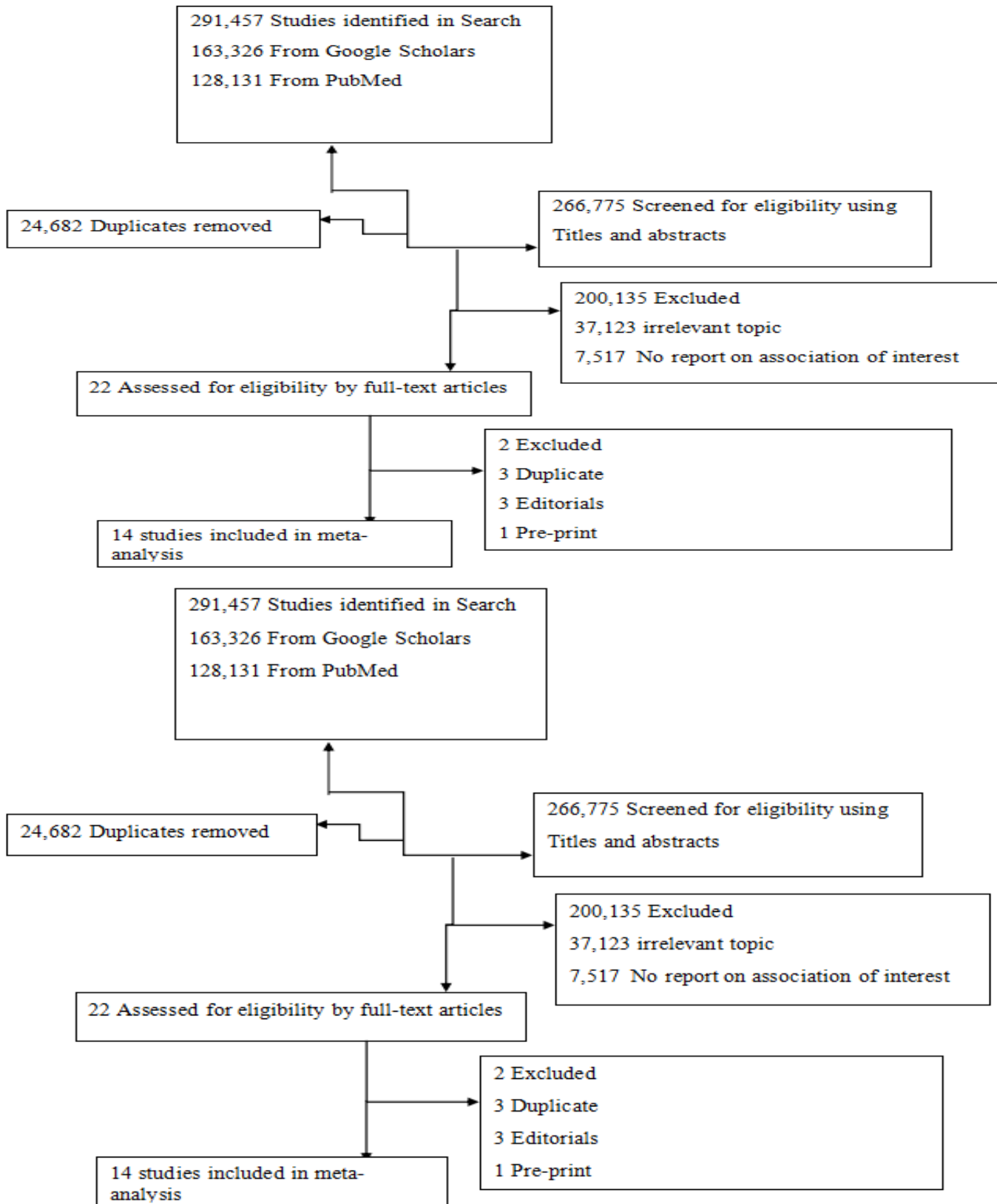


Figure 1: Flow Chart Showing Data Extraction on Meta-Analysis on the risk of chronic mental health conditions among young adults.

4. Data analysis

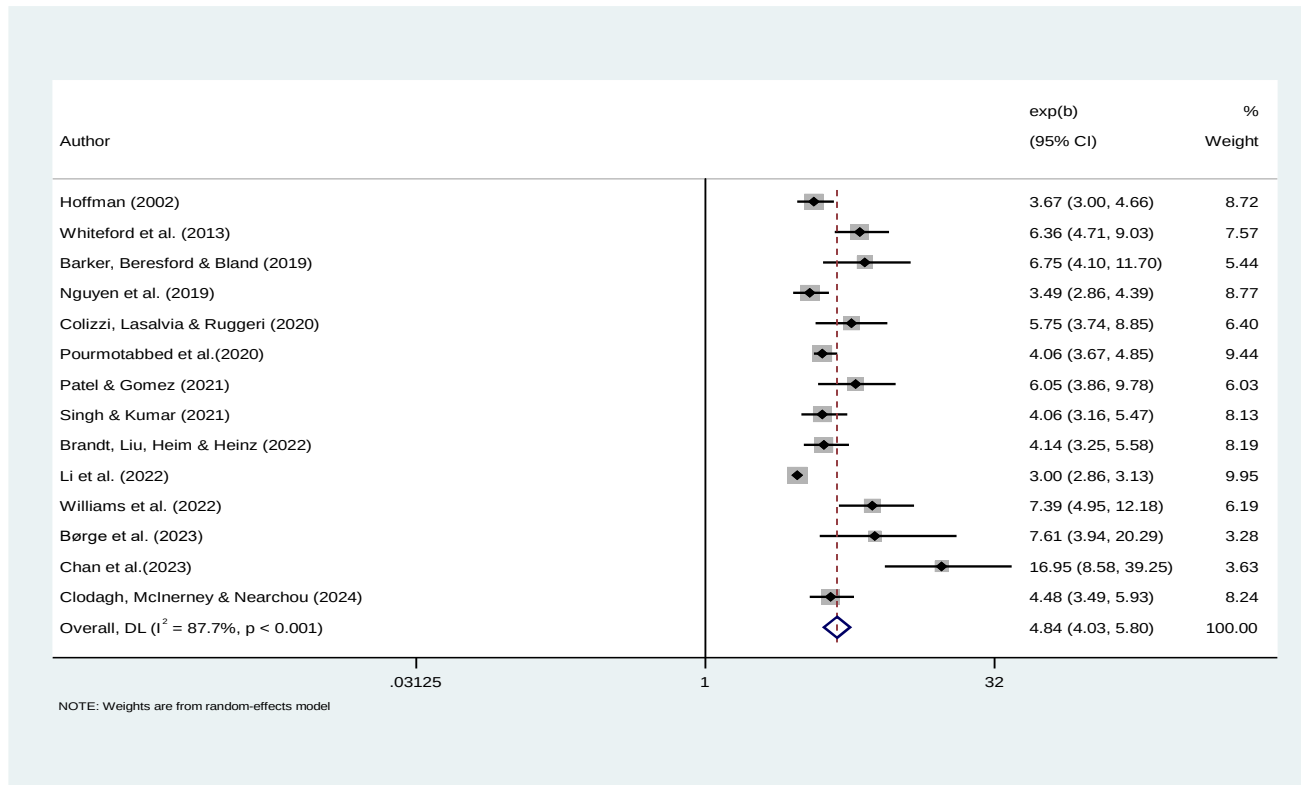


Figure 2: Forest plot of the meta-analysis on the risk of chronic mental health conditions among young adults

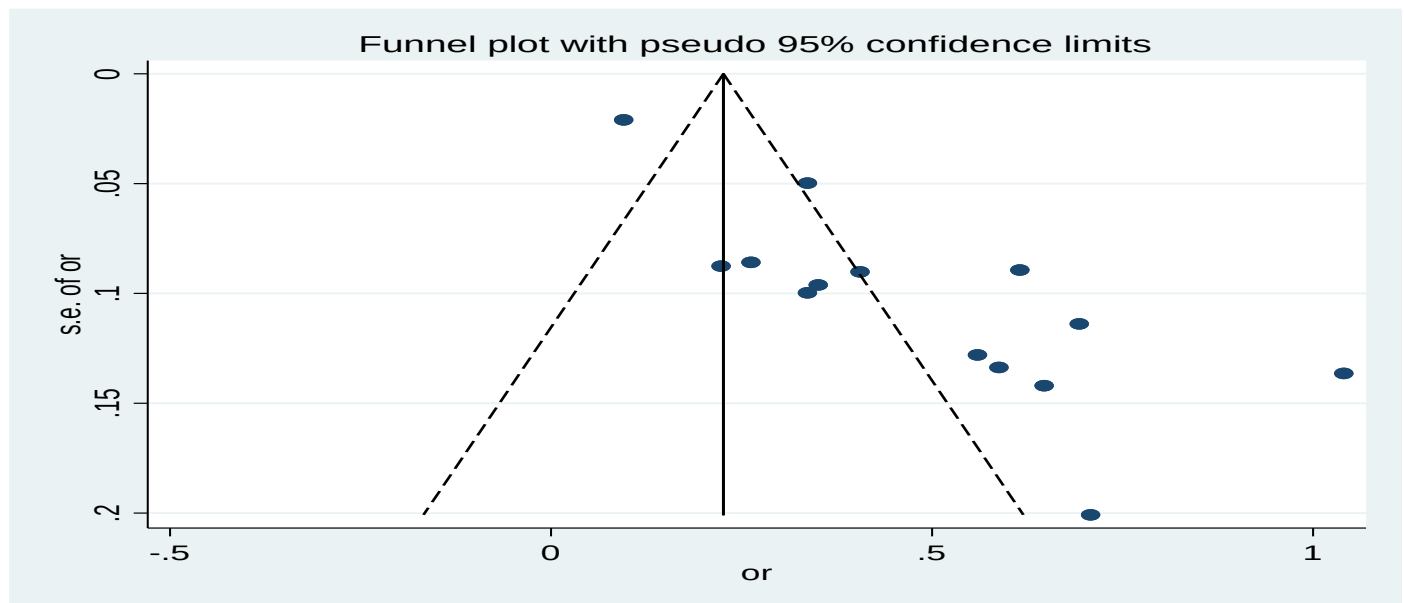


Figure 1: Funnel Plot of the Meta-analysis of the Risk of Chronic Mental Health Conditions in Young Adults, showing Publication Bias

5. Discussion

The meta-analysis pooled data from 14 studies and revealed statistically significant associations between identified risk factors and chronic mental health conditions in young adults ($z = 17.043$, $p < 0.001$). Odds ratios (ORs) from individual studies ranged from 1.10 to 2.83, highlighting variability in the strength of associations among the studies. For example, Chan et al., (2023) reported the highest OR (2.83; 95% CI: 2.15–3.67), suggesting strong links between mental disorders and early risk factors. Conversely, Li et al. (2022) reported a

lower OR (1.10; 95% CI: 1.05–1.14), showing minimal but significant associations. High heterogeneity was observed ($I^2 > 50\%$), indicating significant variability among the included studies. The random-effects model using the DerSimonian-Laird estimate was appropriately applied to account for this variability and provide a generalized estimate across studies. Sources of heterogeneity include variations in study design, sample sizes, diagnostic tools, and study populations.

The funnel plot analysis in Figure 3 reveals some asymmetry, suggesting potential publication bias. Smaller studies with null findings may be underrepresented, leading to an overestimation of pooled effect sizes.

Social isolation and childhood abuse were consistently identified as significant contributors to chronic mental health issues. For instance, Brandt et al. (2022) reported an OR of 1.42 (95% CI: 1.18–1.72), indicating the impact of social stressors. Food insecurity was associated with depression, as highlighted by Pourmotabbed et al. (2020), with an OR of 1.40 (95% CI: 1.30–1.58).

The findings underscore the importance of early interventions aimed at mitigating risk factors such as childhood abuse, social isolation, and economic disparities. 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.

The consistent association between social and psychological stressors and mental health conditions calls for integrated mental health care models. These should include routine screening for risk factors such as abuse history and social support systems during adolescence and early adulthood. Group therapy and multidisciplinary care approaches were identified as effective mechanisms for improving outcomes in individuals with chronic mental health conditions.

The observed heterogeneity highlights the need for standardized methodologies in future studies. Consistent diagnostic tools and clear definitions of risk factors are crucial for improving comparability. Longitudinal studies are recommended to establish causality and to understand the temporal dynamics of risk factor exposure and mental health outcomes. The inclusion of both fixed and random-effects models ensured the robustness of the findings, despite the high heterogeneity. The use of a large sample size across studies improved the generalizability of the results.

Potential publication bias and heterogeneity among the included studies may limit the precision of the pooled estimates. Furthermore, reliance on self-reported data in some studies may introduce recall bias. Policymakers should prioritize mental health funding and awareness campaigns, emphasizing stigma reduction and support for vulnerable populations. For example, addressing the stigma associated with mental illness through educational initiatives can enhance help-seeking behavior.

Collaborative efforts between health sectors and community organizations are essential for implementing comprehensive interventions targeting identified risk factors. Additional studies exploring the impact of emerging factors like screen time and digital isolation on mental health are warranted. Li et al. (2022) emphasized the significance of these factors during the COVID-19 pandemic. Expanding research to include diverse cultural and geographical settings will provide a broader understanding of how environmental and societal influences shape mental health trajectories.

6. Conclusion

This study underscores the critical role that early interventions play in addressing risk factors such as social isolation, childhood abuse, and food insecurity to mitigate the burden of chronic mental health conditions in young adults. The findings emphasize the need for integrated care models that combine clinical, social, and

policy-level interventions. Although the meta-analysis revealed significant associations, the presence of heterogeneity and potential biases highlights the need for standardized methodologies in future research.

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