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Pathways to Depression: A Multidimensional Composite Analysis of Socioeconomic Inequalities in a Population-Based Study

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ABSTRACT

Background: Socioeconomic factors are recognized as key contributors to the risk of depression among adults and older populations. However, socioeconomic status (SES) is often measured using single indicators, which may not capture its multidimensional nature. Moreover, the mechanisms through which socioeconomic conditions influence depression remain insufficiently explored. This study aimed to examine the pathways linking socioeconomic inequalities to depression using a multidimensional composite measure of SES.

Subjects and Method: A cross-sectional analysis was conducted using data from the 2023 Indonesian Health Survey, a nationally representative population-based survey. SES was constructed using principal component analysis (PCA) based on wealth index, education level, employment status, participation in government social protection programs, and provincial-level income inequality (Gini index). Path analysis was performed to assess direct and indirect relationships between SES, physical activity, comorbidity, and depression. All analyses were conducted using STATA 17.

Results: Higher SES was associated with a lower risk of depression. Significant pathways were observed from SES to depression both directly (β= -0.06; 95% CI= -0.07 to -0.06; p <0.001) and indirectly through comorbidity (β= -0.03; 95% CI= -0.03 to 0.02; p <0.001).

Conclusion: Socioeconomic inequalities play a critical role in shaping depression risk through multiple pathways.

Keywords: depression, socioeconomic inequalities, Gini index, household wealth index, principal component analysis

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BACKGROUND

Socioeconomic status (SES) represents a multidimensional construct that reflects an individual's or household's position within society, incorporating aspects such as income, educational attainment, occupational status, and broader social standing. As a fundamental social determinant of health, SES plays a crucial role in shaping access to resources, opportunities, and living conditions, thereby shaping health outcomes and contributing to persistent health inequalities (Sacre et al., 2023).

A growing body of evidence has consistently demonstrated strong associations between SES and various health outcomes (Ferreira et al., 2023; Martínez-Jiménez et al., 2025), including findings from Indonesia (Arulsamy et al., 2025; Nurokhmah et al., 2025; Pasambo et al., 2025). However, there is no universally accepted standard for measuring SES, as different indicators may capture distinct dimensions of social and economic positioning (Buder et al., 2024). While some studies have proposed composite indices to better reflect socioeconomic disparities, particularly among older adults, these approaches are not always directly applicable in low- and middle-income settings due to differences in lifestyle, infrastructure, and health system characteristics (Darin-Mattsson et al., 2017; Sacre et al., 2023).

Furthermore, while prior research has identified key domains for SES measurement, such as education, income, employment, household characteristics, and access to services (Leite et al., 2022; American Psychological Association, 2026), there remains limited integration of these dimensions across multiple levels, including individual, household, and structural contexts.

Methodologically, approaches such as Principal Component Analysis (PCA) have been widely used to construct composite SES indices, enabling the integration of multiple indicators into a single measure while preserving the underlying factor structure (Sacre et al., 2023). However, few studies have applied such multidimensional SES measures to explore the mechanisms linking socioeconomic inequalities to mental health outcomes, particularly depression. Existing evidence suggests that socioeconomic disadvantage is an important risk factor for depression among adults and older populations, yet the pathways through which SES operates across different levels remain insufficiently understood.

To address these gaps, this study adopts a multidimensional and multilevel approach to SES by integrating individual characteristics (education level, employment status, and participation in government social protection programs), household conditions (wealth index based on asset ownership), and structural factors (provincial Gini index stratified by urban and rural areas to capture income inequality). These data are derived from the Indonesian Health Survey, which provides comprehensive information on health status, health behaviors, and participation in social and health programs.

By combining multiple dimensions of SES within a unified analytical framework, this study offers a more comprehensive understanding of how socioeconomic inequalities are structured and how they influence mental health outcomes. Such an approach is expected to provide more contextually relevant evidence for low- and middle-income settings, particularly Indonesia, and to inform more targeted and equitable public health interventions.

SUBJECTS AND METHOD

1. Study materials

This study investigated the pathways linking socioeconomic inequalities to depression using a multidimensional composite measure of socioeconomic status (SES). A cross-sectional design was applied, and path analysis was used to assess both direct and indirect associations among variables within the proposed conceptual framework.

Data were obtained from the Indonesian Health Survey (Survei Kesehatan Indonesia, 2023), a nationally representtative survey that captures information on health outcomes, health-related behaviors, and social and structural determinants of health. The analytical sample consisted of individuals aged 18 years and above.

A total of 589,083 individuals were retained for analysis following the selection of relevant study variables. Cases with incomplete responses on key measurements (depression) were excluded to maintain data quality and reliability of the findings.

2. Study variables

2.1. Depression was defined as a mood disorder that causes a persistent feeling of sadness and loss of interest Chand and Arif, 2023). It was assessed using a 30-item questionnaire with Likert-scale responses, and the total score was calculated by summing all items, with higher scores indicating more severe depressive symptoms.

2.2. Marital status was defined as the participant's current marital condition and coded as 0 for not married (single, divorced, or widowed) and 1 for married.

2.3. Comorbidity was defined as the co-occurrence of chronic conditions, including tuberculosis, diabetes mellitus, hypertension, cardiovascular disease, stroke, and renal disease. All data were collected through self-reported responses provided by the participants. A binary classification was applied, where 0 indicated the absence of comorbidity (none or a single condition) and 1 indicated the presence of multimorbidity (two or more conditions).

2.4. Physical activity was defined as any bodily movement that requires energy expenditure and was classified based on intensity and frequency. It was measured using self-reported information on participation in vigorous and moderate activities in daily living, and quantified in metabolic equivalent of task (MET) minutes per week.

2.5. Socioeconomic status (SES) refers to a composite measure of an individual's economic and sociological standing in society (Braveman et al., 2005; Villalba, 2024). It was constructed using principal component analysis (PCA) based on four indicators: (1) education level, (2) employment status, (3) participation in government social protection programs, (4) wealth index, and (5) Gini index by province.

2.6. Place of living was defined as the residential setting of participants and categorized as urban or rural based on the classification of the Indonesian Central Bureau of Statistics.

3. Data analysis

3.1. Univariate analysis

Univariate analysis was conducted to describe the distribution and characteristics of each variable included in the study. Categorical variables were presented as frequencies and percentages, while continous variables were summarized using means and standard deviations.

3.2. Principal component analysis (PCA)

The wealth index was derived from a principal component analysis (PCA) of 16 household asset items. Prior to the analysis, items with extreme ownership distributions (i.e., less than 10% or greater than 90%) were excluded, including mobile phones, landline telephones, and water heaters. These exclusions were applied to avoid limited variability that could bias the PCA results (Xie et al., 2023). Subsequently, tetrachoric correlation analysis was conducted to account for the binary nature of the asset variables. The results indicated that ownership of certain assets, such as boats, motorboats, land, and livestock, had negative correlations. These negative loadings suggest that such assets are more commonly owned by households in specific geographical or socioeconomic contexts, such as rural or coastal areas, leading to uneven distribution across the population. Therefore, these items were excluded from further analysis. A total of nine asset items were retained and included in the final PCA. The first principal component was selected to represent the wealth index, and the resulting scores were categorized into two groups based on the median split, classifying households as poor and rich.

Data on ownership of a social assistance card (*Kartu Keluarga Sejahtera/ Kartu Perlindungan Sosial*), as well as participation in government social protection programs, including conditional cash transfers (*Program Keluarga Harapan*, PKH), in-kind food assistance (*Bantuan Pangan Non-Tunai*, BPNT), and unconditional cash transfers (*Bantuan Langsung Tunai*, BLT), were included in the PCA to construct a composite variable representing government social protection programs. The first principal component was extracted and used to generate a composite score. This score was subsequently categorized into a binary variable, classifying households into "non-beneficiaries" and "beneficiaries" of social protection programs.

After all SES indicators were prepared and coded as binary variables, Principal Component Analysis (PCA) was performed to construct a composite SES measure. The first principal component was retained to represent SES, as it accounted for the largest proportion of variance among the included indicators.

The resulting SES scores were standardized and subsequently categorized into four groups based on quartiles: poor (lowest quartile), lower-middle (second quartile), upper-middle (third quartile), and rich (highest quartile). This categorization was applied to facilitate interpretation and to capture the gradient of socioeconomic inequalities across the study population.

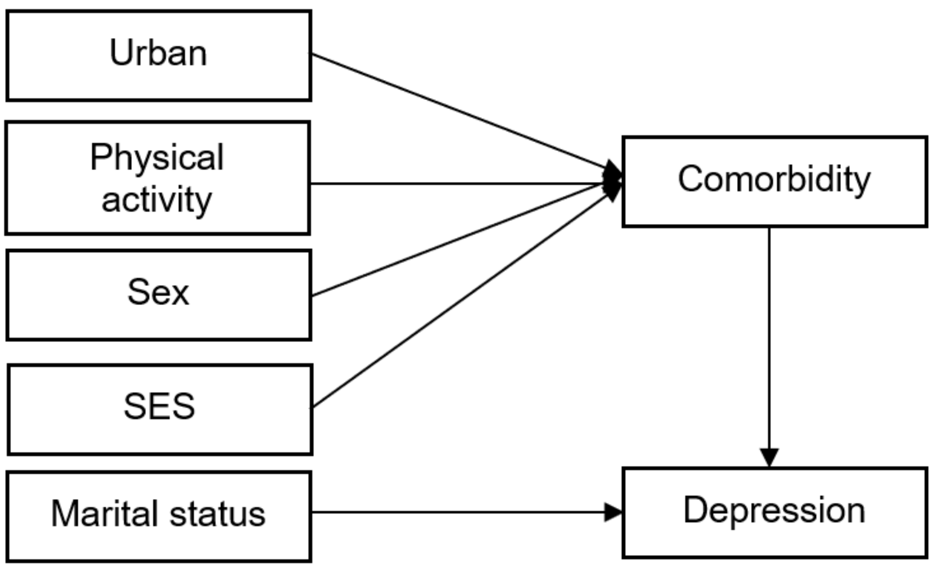

Figure 1. The hypothesized model served as the initial conceptual basis for the development and specification of the path model.

3.3. Path analysis

Path analysis was employed to investigate the direct and indirect pathways linking socioeconomic status to depression, allowing for the simultaneous estimation of multiple relationships within the model (Lleras, 2005; Streiner, 2005). The analysis followed several steps.

First, model specification was conducted by developing a theoretical framework based on prior evidence and conceptual assumptions (Figure 1). Second, model identification was performed by classifying variables into exogenous and endogenous variables. Third, model estimation was carried out to assess the hypothesized relationships among variables. Fourth, model evaluation was conducted using goodness-of-fit indices to determine how well the model fit the data. Finally, model re-specification was undertaken, if necessary, based on theoretical justification and model fit results (Kang and Ahn, 2021; Williams et al., 2022). **Figure 1** was adapted from several studies that identified correlations among the variables included in the model (Zhao et al., 2022; Mu et al., 2024; Ochnik et al., 2024).

4. Ethical consideration

Ethical approval for this study was obtained from the Ethics Committee of the Faculty of Health Sciences, Universitas Muhammadiyah Surakarta, Indonesia. The committee confirmed that the study adheres to the seven ethical standards established by the World Health Organization (WHO, 2011). This approval is documented under reference number 2000/KEPK-FIK/II/2026.

RESULTS

1. Univariate analysis

The descriptive findings reveal a seemingly paradoxical pattern (Table 1). Although the overall mean depression score was low, the population exhibits substantial socioeconomic disparities across multiple dimensions, including education, employment, household wealth, and structural income inequality. This contrast suggests that the burden of depression may not be evenly distributed, but instead concentrated within specific vulnerable subgroups.

A clear socioeconomic gradient is evident. More than half of the participants had low educational attainment (55.30%), one-third were unemployed (33.87%), and the largest proportion of households fell into the poorest wealth category (34.57%). In parallel, a considerable proportion of individuals relied on government social protection programs, indicating the presence of underlying economic vulnerability despite broad population coverage. At the macro level, the observed Gini index (mean = 0.34) reflects moderate but meaningful income inequality, further reinforcing the presence of structural disparities.

These multidimensional SES indicators coexist within the same population, suggesting that socioeconomic disadvantage operates not only at the individual or household level but also within broader structural contexts. Such layered inequalities are likely to shape differential exposure to stressors, access to resources, and coping capacities, all of which are critical pathways influencing mental health outcomes.

Therefore, while the average level of depression appears low, these findings raise the possibility of hidden inequalities in depression risk, where disadvantaged groups may disproportionately experience higher symptom burden. This underscores the importance of moving beyond single-indicator approaches and adopting a multidimensional perspective of SES to better capture its complex relationship with depression.

Table 1. Distribution of depression and socioeconomic inequalities across individual, household, and structural levels

Study variables	n	%
Depression (score) (*mean, SD; min-max)*	0.66 (2.01)	(0-30)
Sex		
Female	321,993	54.66
Male	267,090	45.34
Age (years old), (*mean, SD; min-max)*	44.01 (14.88)	(18-112)
18-39 years old	241,415	40.98
40-50 years old	153,853	26.12
51-59 years old	97,746	16.59
60-84 years old	93,790	15.92
85+ years old	2,279	0.39
Marital status		
Unmarried/ living alone	131,861	22.38
Married/ living with spouse	457,222	77.62
Education level		
Low (<Senior high school)	325,762	55.30
High (≥Senior high school)	263,321	44.70
Employment		
Unemployed	199,544	33.87
Employed	389,539	66.13
Comorbidity		
None or has 1 disease	576,778	97.91
Has 2 or more diseases	12,305	2.09
Type of diseases		
Tuberculosis		
No	587,277	99.69
Yes	1,806	0.31
Diabetes mellitus		
No	574,321	97.49
Yes	14,762	2.51
Hypertension		
No	536,184	91.02
Yes	52,899	8.98
Cardiovascular disease		
No	582,349	98.86
Yes	6,734	1.14
Stroke		
No	583,516	99.05
Yes	5,567	0.95
Kidney disease		
No	587,857	99.79
Yes	1,226	0.21
Household wealth index		
Poor	203,635	34.57
Lower-middle	116,957	19.85
Upper-middle	120,739	20.50
Rich	147,752	25.08
Government social protection program		
Social Protection Card *(Indonesian term: Kartu Keluarga Sejahtera/Kartu Perlindungan Sosial)*		
No	454,403	77.14

Study variables	n	%
Yes	134,634	22.86
Conditional Cash Transfer Program *(Indonesian term: Program Keluarga Harapan, PKH)*		
No	499,685	84.83
Yes	89,352	15.17
In-kind food assistance program *(Indonesian term: Bantuan Pangan Non Tunai)*		
No	519,514	88.20
Yes	69,523	11.80
Unconditional cash transfer program *(Indonesian term: Bantuan Langsung Tunai, BLT)*		
No	518,298	87.99
Yes	70,739	12.01
Gini index *(mean, SD; min-max)*	0.34 (0.06)	(0.20-0.45)
Quartil 1: Low income inequality	317,530	53.90
Quartil 2: High income inequality	271,553	46.10
Place of living		
Rural	269,680	45.78
Urban	319,403	54.22

2. Path analysis

2.1. Model specification

The proposed path model (**Figure 1**) was specified to examine the direct and indirect relationships between socioeconomic status (SES) and depression within a multivariable framework. This specification is grounded in the social determinants of health framework, which posits that socioeconomics condition shape health outcomes through differential access to resources, exposure to risks, and coping capacities (Gordon-Achebe et al., 2024; Salem and Robenson, 2025).

2.2. Model identification

Figure 1 contains two endogenous variables, five exogenous variables, six paths, and two residual variables.

2.3. Model fit

The hypothesized path model presented in **Figure 1** was overidentified (df ≥1), allowing model testing. However, the model exhibited poor goodness-of-fit, as evidenced by the significant chi-square value (χ^2 = 3,868.13, $p < 0.001$). Although the model showed low error values, with RMSEA= 0.04 and SRMR= 0.01, the CFI= 0.83, TLI= 0.61, and CD= 1.6% indicated inadequate model fit (Table 2).

2.4. Model estimation

The path analysis model presented in **Figure 1** indicated that depression was directly and positively associated with comorbidity (β = 0.12; 95% CI: 0.12 to 0.13; p<0.001) and directly and negatively associated with marital status (β = -0.06; 95% CI: -0.06 to -0.05; p < 0.001). The model further demonstrated that depression was indirectly associated with male sex (β = -0.03; 95% CI: -0.03 to -0.03; p < 0.001), physical activity (β = -0.08; 95% CI: -0.08 to -0.07; p <0.001), socioeconomic status (SES) (β = -0.03; 95% CI: -0.04 to -0.03; p < 0.001), and residential place (β = 0.06; 95% CI: 0.06 to 0.06; p < 0.001) through comorbidity.

Table 2. Standardized path coefficients for the hypothesized model of socioeconomic disadvantage on depression

Dependent variables		Independent variables	Standardized coef. (β)	95% CI	p
Direct effect					
Depression	←	Comorbidity	0.12	0.12 to 0.13	<0.001
	←	Marital status (married)	-0.06	-0.06 to -0.05	<0.001
Indirect effect					
Comorbidity	←	Physical activity (MET-min/week)	-0.08	-0.08 to -0.07	<0.001
	←	High SES	-0.03	-0.04 to -0.03	<0.001
	←	Sex (male)	-0.03	-0.03 to -0.03	<0.001
	←	Place of living (urban)	0.06	0.06 to 0.06	<0.001
Goodness of fit indices					
N observation: 582,787; df= 10; Chi²= 3,868.13; p <0.001; RMSEA= 0.04; CFI= 0.83; TLI= 0.61; SRMR= 0.02; CD= 1.6%.					

2.5. Re-specification model

Since the hypothesized model shown in **Figure 1** did not meet the recommended model fit criteria, a series of model modifications were conducted. The modified models were evaluated and compared with the original hypothesized model to determine whether an improved and more parsimonious model could be achieved.

Model modification was performed using a combination of data-driven and theory-driven approaches. Potential associations were first identified based on modification indices generated in Stata. Subsequently, each suggested modification was carefully evaluated against relevant theoretical frameworks and evidence from previous studies before being incorporated into the model. This approach ensured that model revisions were not solely data-driven but remained theoretically meaningful and empirically justified.

Although the modification indices indicated potential improvements in model fit by adding paths from depression to comorbidity (standardized expected parameter change [EPC] = -0.39, p < 0.001) and from marital status to comorbidity (standardized EPC = 0.02, p < 0.001), these associations were not supported by the underlying theoretical framework or prior empirical evidence. Consequently, the suggested modifications were rejected.

Other recommendations from the modification indices suggested adding direct paths from physical activity (standardized EPC= -0.02, p < 0.001), sex (standardized EPC = -0.05, p < 0.001), and socioeconomic status (SES) (standardized EPC= -0.06, p < 0.001) to depression. Unlike the previously suggested pathways, these associations were theoretically plausible and supported by prior research indicating that physical activity, sex, and socioeconomic status are important determinants of depression. Therefore, these pathways were considered for inclusion in the modified model and subsequently evaluated through model comparison procedures.

In the re-specified path model, socioeconomic status (SES) was modelled as a key endogenous variable influenced by urban residence (**Figure 2**). The inclusion of this pathway was supported by both theoretical considerations and previous empirical studies suggesting that residential location plays an important role in shaping socioeconomic conditions through differential access to employment opportunities, education, infrastructure, and social resources. This assumption is consistent with evidence suggesting that place of residence, particularly urban–rural disparities, affects access to education, employment, and economic resources (Guo et al., 2024; Assari et al., 2025; Jia and Deng, 2026).

2.5.1. Model specification

Several exogenous variables were included in the model, namely physical activity, sex, and urban residence. Physical activity was incorporated based on behavioral health theories that highlight its protective role against depression, both directly and through its influence on physical health conditions (Wanjau et al., 2023). Sex was included to account for biological and gender-related differences in mental health vulnerability and exposure to socioeconomic stressors. Marital status was also included as an exogenous predictor of depression, supported by social support theory, which emphasizes the buffering effect of social relationships on psychological distress (Qadir et al., 2013; Amin et al., 2025). Overall, the model integrates individual, behavioral, and structural dimensions to capture the complex and interconnected pathways through which socioeconomic inequalities may influence depression.

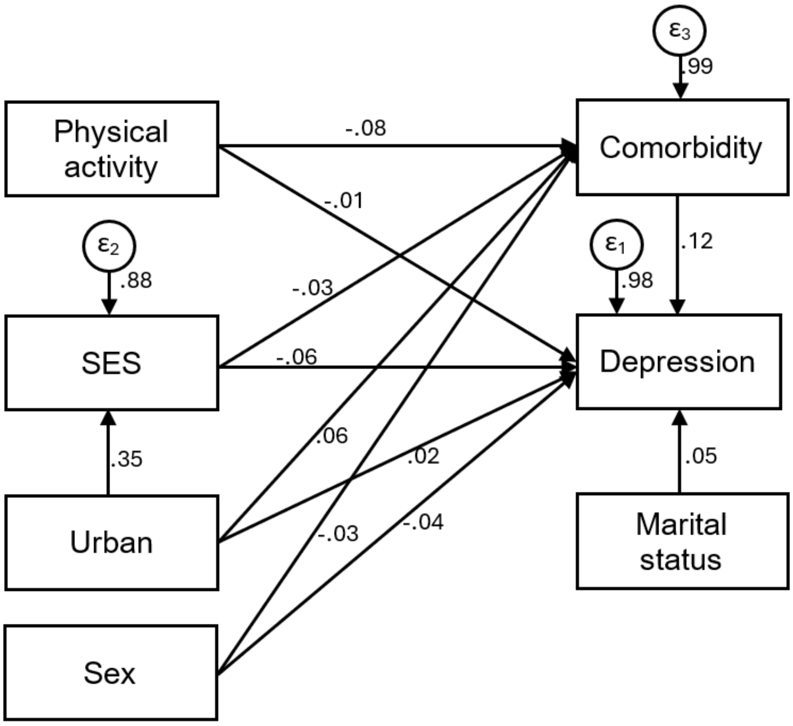

Figure 2. Direct and indirect paths between socioeconomic status and other variables on predicting depression (selected model)

2.5.2. Model identification

Figure 2 presents a modified path model consisting of exogenous and endogenous variables. The exogenous variables include sex and urban residence. The endogenous variables comprise socioeconomic status (SES), physical activity, comorbidity, marital status, and depression. The model specifies 11 structural paths representing the hypothesized relationships among variables. Each endogenous variable is associated with a residual variable, reflecting unobserved influences not captured by the model. The structural model was over-identified (degree of freedom= 17), indicating that the model is statistically estimable and suitable for hypothesis testing (**Table 3**).

2.5.3. Model fit

We added paths from sex, SES, physical activity, and urban living to depression based on previous studies that reported associations between sex and depression (de Breij et al., 2022), SES and depression (Wang et al., 2024), physical activity and depression (Zhao et al., 2024), and place of living and depression (Olea et al., 2025). We also added a path between place of living and SES, consistent with findings reported by Balen et al. (2010).

The model fit indices for final path model (**Figure 2**) indicated an overall acceptable fit (**Table 3**). The chi-square test was statistically significant ($\chi^2 = 5753.56$, $p < 0.001$), which is common in large samples due to its sensitivity to sample size. The RMSEA value of 0.05 suggested a good fit, while the CFI of 0.94 indicated an acceptable to good model fit. The SRMR value of 0.02 further supported a good fit of the model. However, the TLI value of 0.79 was below the recommended threshold, indicating some degree of model misspecification. Despite this, the combination of fit indices suggests that the model provides an adequate representation of the data. The coefficient of determination (CD) indicated that approximately 13.7% of the variance in the endogenous variables was explained by the model.

2.5.4. Model estimation

Comorbidity emerged as the strongest proximal determinant of depression, while socioeconomic status exerted both direct and indirect effects through comorbidity, highlighting the importance of socioeconomic pathways in mental health.

Table 3. Standardized path analysis estimates linking socioeconomic disadvantage to depression after re-specification (selected model)

Dependent variables		Independent variables	Standardized coef. (β)	95% CI	p
Direct effect					
Depression	←	Sex (male)	-0.04	-0.05 to -0.04	<0.001
	←	Marital status (married)	-0.05	-0.06 to -0.05	<0.001
	←	Comorbidity	0.12	0.12 to 0.12	<0.001
	←	Physical activity (MET-min/week)	-0.01	-0.01 to -0.01	<0.001
	←	High SES	-0.06	-0.07 to -0.06	<0.001
	←	Place of living (urban)	0.02	0.02 to 0.03	<0.001
Indirect effect					
Comorbidity	←	Physical activity (MET-min/week)	-0.08	-0.08 to -0.07	<0.001
	←	High SES	-0.03	-0.03 to -0.02	<0.001
	←	Sex (male)	-0.03	-0.03 to -0.03	<0.001
	←	Place of living (urban)	0.06	0.05 to 0.06	<0.001
High SES	←	Place of living (urban)	0.82	0.81 to 0.82	<0.001
Total effect					
Depression	←	Sex (male)	-0.19	-0.20 to -0.18	<0.001
	←	Marital status (married)	-0.26	-0.27 to -0.24	<0.001
	←	Comorbidity	0.57	0.56 to 0.59	<0.001
	←	High SES	-0.11	-0.12 to -0.11	<0.001
	←	Physical activity (MET-min/week)	-0.01	-0.01 to -0.01	<0.001
	←	Place of living (urban)	0.03	0.02 to 0.04	<0.001

Dependent variables		Independent variables	Standardized coef. (β)	95% CI	p
Comorbidity	←	Sex (male)	-0.03	-0.03 to -0.02	<0.001
	←	Physical activity (MET-min/week)	-0.01	-0.01 to -0.01	<0.001
	←	High SES	-0.01	-0.01 to -0.01	<0.001
	←	Place of living (urban)	0.04	0.03 to 0.04	<0.001
Goodness of fit indices					
N observation: 582,787; df= 17; Chi^2= 5,753.56; p <0.001; RMSEA= 0.05; CFI= 0.94; TLI= 0.79; SRMR= 0.02; CD= 13.7%.					

2.5.5. *Model re-specification*

No further model re-specification was deemed necessary, as the goodness-of-fit indices indicated an acceptable model fit and the hypothesized paths were supported by previous studies and theoretical frameworks. However, the final model presented in this study was derived from an iterative re-specification process, involving several adjustments through the addition and removal of paths. These modifications were guided by both statistical considerations and theoretical justification, and the revised model was subsequently tested and selected as the final model.

RESULTS

1. Socioeconomic status and depression

The pathway analysis reveals a nuanced mechanism linking socioeconomic status (SES), comorbidity, and depression. Higher SES was directly associated with lower levels of depression, indicating a protective effect of socioeconomic advantage. This finding is consistent with the well-established social gradient in health, where individuals with greater access to resources, opportunities, and coping capacities tend to experience better mental health outcomes (Salem et al., 2025).

At the structural level, urban residence was positively associated with higher SES, highlighting the role of spatial and contextual factors in shaping socioeconomic opportunities. Urban areas typically provide greater access to education, employment, and healthcare, thereby facilitating higher socioeconomic positioning. However, this pattern must be interpreted within the broader context of regional inequality. Regional disparities remain a persistent and global issue, where development strategies that prioritize macroeconomic growth often overlook uneven distribution across regions (Soebagyo et al., 2019). As a result, urban areas may concentrate resources and opportunities, while rural areas experience relative deprivation, reinforcing socioeconomic inequalities.

An additional indirect pathway was observed. Higher SES was positively associated with comorbidity, which in turn increased the risk of depression. A previous study has suggested that greater wealth may affect individual and population health in contrasting ways, where higher socioeconomic advantage can be associated with increased detection or reporting of chronic conditions (Olejnik and Żółtaszek, 2023).

A plausible explanation for this mechanism is that individuals with higher SES may be more exposed to lifestyle-related risk factors, such as sedentary behavior, dietary patterns, and work-related stress, which can contribute to the development of chronic conditions. This finding is consistent with previous research indicating that certain forms of socioeconomic advantage may paradoxically increase the risk of multimorbidity through lifestyle and behavioral pathways (Chauhan et al., 2022).

2. Multimorbidity and depression

Our path model showed that multimorbidity significantly influences depression. This finding is consistent with previous studies, including Lin et al. (2021), which reported a strong association between multiple chronic conditions and depressive symptoms. Evidence from longitudinal research further supports this relationship, demonstrating that individuals with multimorbidity have a higher risk of developing mental health disorders compared to those without chronic diseases (Yan et al., 2021). In addition, prior studies have shown a dose–response relationship, where an increasing number of chronic conditions is associated with a greater likelihood of depression and other mental health problems (Barnett et al., 2012).

Several mechanisms may explain this association. Chronic illnesses are often accompanied by persistent symptoms such as pain, discomfort, and fatigue, as well as the burden of ongoing treatment, including long-term medication use and frequent healthcare visits. These factors can negatively affect mood and overall well-being. Furthermore, the cumulative burden of managing multiple conditions may increase psychological stress, reduce quality of life, and limit functional capacity, thereby elevating vulnerability to depressive symptoms (Ren et al., 2024).

3. Physical activity and depression

The results of this study demonstrated a direct association between physical activity and depression, indicating that higher levels of physical activity are linked to lower levels of depressive symptoms. This finding is consistent with evidence from a systematic review, which highlights that improving physical functioning and promoting social support are key strategies in reducing loneliness and depression (Sulandari et al., 2024). Furthermore, engaging in regular physical activity, performing exercise tailored to individual conditions, or participating in community-based exercise programs has been shown to effectively reduce depressive symptoms (Kurniawati and Maulina, 2024; Liu et al., 2025).

We also examined an indirect pathway from physical activity to depression mediated by multimorbidity. The findings suggest that higher levels of physical activity are associated with a lower likelihood of multimorbidity, which in turn is linked to reduced depressive symptoms. This indicates that physical activity may exert its protective effect on mental health not only through direct mechanisms but also indirectly by preventing or reducing the burden of multiple chronic conditions (Trisnowiyanto & Fadli, 2023).

A study by Wen and Yang (2025) reported that individuals who more frequently engaged in moderate-intensity physical activity (PA) were less likely to exhibit multimorbidity patterns. Previous studies have also demonstrated that moderate-intensity PA can effectively reduce systemic inflammation and improve metabolic indicators (Arem et al., 2015; Son et al., 2023). In this context, regular physical exercise contributes to overall health not only through direct physiological benefits but also by mitigating the risk of chronic conditions. Although reductions in body mass and adiposity are not the primary outcomes of exercise, it plays a crucial role in mediating obesity-related diseases, including type 2 diabetes and cardiovascular disease (Pinckard et al., 2019).

4. Sex (male) and depression

Our path analysis found that there was difference of sex on both presence of comorbidity and depression level. Previous study also reported that the odds of having a specific comorbid condition differ between the sexes (Veenendaal et al., 2019; Dronkers et al., 2022; Reemst et al., 2022).

This study demonstrated that sex has a direct and negative association with depression, indicating that males tend to have lower depression scores compared to females. This finding is consistent with previous evidence showing that major depressive disorder is significantly more prevalent in women, with approximately twice the risk compared to men (Kendler et al., 2006). From a biological perspective, sex differences in depression may also be explained by mechanisms at the in vivo level, where disruptions in the development of the hypothalamic–pituitary–adrenal (HPA) axis during fetal life are associated with long-term alterations in brain activity and hormonal regulation. These neuro-endocrine differences contribute to the observed disparities in depression risk between men and women (Tobet et al., 2013).

In addition, the path analysis estimated an indirect relationship between sex and depression through the mediator of presence of comorbidity. The findings indicate that males have a lower likelihood of experiencing comorbid conditions compared to females. This, in turn, contributes to the lower risk of depression among males, as the presence of comorbidity is known to exacerbate mental health conditions. Therefore, sex differences in depression are not only observed through direct pathways but are also mediated by differences in physical health status.

The underlying mechanisms behind these sex disparities are multifactorial, encompassing physiological, genetic, and environmental factors. Emerging evidence suggests that human biological systems exhibit sex-specific patterns of gene expression during critical developmental periods, including processes related to gene regulation. These differences are partly influenced by androgen- and estrogen-responsive elements, which can modulate gene activity and downstream biological functions. Consequently, such sex-specific regulatory mechanisms may contribute to variations in the incidence and manifestation of a wide range of conditions, including cardiovascular, metabolic, immune, neurological, and mental health disorders, ultimately shaping differential vulnerability to depression between males and females (Shi et al., 2024).

5. Marital status and depression

Our study assessed the social effect on depression as represented by marital status. The findings indicate that individuals who are married or living with a spouse have lower levels of depression compared to those who are unmarried, widowed, or divorced.

This finding is consistent with previous studies reporting an association between marital status and depression. Darmawati et al. (2026) found that strong social interaction with a spouse can buffer stress and reduce depressive symptoms. Similarly, Pan et al. (2022) reported that individuals who are separated, divorced, widowed, or never married are at a higher risk of experiencing depressive symptoms compared to married individuals. Never-married middle-aged and older adults tend to experience prolonged loneliness, reduced social support, and lower self-confidence, which may increase their vulnerability to depression. In addition, widowed individuals often face diminished social support, increased feelings of loneliness and stigma, and economic hardship, which may limit their access to healthcare and basic needs, thereby further increasing the risk of depression (Mosha and Ngulube, 2024).

6. Urban living and depression

Our path model demonstrated that urban living has a direct association with depression. Urban living may exert this direct effect through multiple interrelated psychosocial and environmental mechanisms. As articulated within the framework of Social Determinants of Health, the residential environment is recognized as a key determinant of mental health, capable of influencing psychological outcomes independently of individual-level factors.

In Indonesia, rapid urbanization, population growth, and economic expansion (Muzayanah et al., 2022) have contributed to increasingly dense and complex urban environments. These settings are characterized by high population density, noise, traffic congestion, and continuous sensory stimulation. Such conditions can induce chronic psychological stress and cognitive overload, potentially disrupting stress-response systems and increasing vulnerability to depressive symptoms (Khairunnisa et al., 2024).

Moreover, despite high population density, urban environments often exhibit social fragmentation and reduced social cohesion (Amalia et al., 2025). Individuals may experience social isolation, weaker interpersonal relationships, and limited emotional support. This “loneliness in crowds” phenomenon has been consistently associated with a higher risk of depression (Heu, 2023).

Urban living is also frequently linked to heightened socioeconomic pressures, including income inequality (van Leeuwen and Földvári, 2016), intense job competition, and rising living costs (Yudhistira et al., 2024). These stressors may lead to financial insecurity and chronic stress, both of which are well-established risk factors for depression (Mumang et al., 2020).

In our study, urban living was found to influence depression indirectly through morbidity. This suggests that the impact of urban environments on mental health is not only direct but also operates through intermediate physical health conditions. Previous studies have reported a high prevalence of comorbid psychological distress among individuals with physical illnesses (Mendenhall et al., 2013). This indirect pathway is consistent with the broader literature indicating that chronic conditions and multimorbidity are strongly associated with depression, as they may reduce functional capacity, increase healthcare burden, and negatively affect mental well-being (Tan et al., 2020; Luo and Wang, 2022). From the perspective of the Social Determinants of Health, urban living can be understood as an upstream determinant that shapes physical health risks, which subsequently mediate its influence on mental health outcomes.

A pathway in our path model suggests that urbanization plays a role in shaping socioeconomic status (SES). This finding is supported by a spatial analysis study in Indonesia, which reported that urbanization positively influences community welfare and urban economic growth (Noviani et al., 2025). Urban areas typically offer greater access to employment opportunities, education, infrastructure, and health services, all of which contribute to improved socioeconomic conditions. Therefore, urbanization may enhance SES by facilitating economic productivity and social mobility. However, the benefits of urbanization may not be evenly distributed, as disparities in income, living conditions, and access to resources can persist within urban populations.

7. Conclusion

This study highlights the complex interplay between socioeconomic, behavioral, and health-related factors in influencing depression. Socioeconomic status (SES) demonstrates a protective effect against depression; however, it also shows an indirect pathway through multimorbidity, suggesting a nuanced and dual mechanism. Multimorbidity emerges as a key determinant of depression, both directly and as a mediator linking other factors such as physical activity, sex, and urban living to mental health outcomes.

Physical activity plays a significant protective role against depression, both directly and indirectly by reducing the risk of multimorbidity. Social factors, particularly marital status, also contribute to mental well-being, with married individuals showing lower levels of depression, likely due to stronger social support. In addition, sex differences indicate that males are less likely to experience depression, partly due to lower comorbidity burden.

Urban living presents both risks and opportunities. While it is associated with higher SES, it also contributes to increased psychological stress, social fragmentation, and higher risk of depression, both directly and indirectly through morbidity. Overall, the findings emphasize that depression is shaped by interconnected pathways involving social determinants, physical health, and behavioral factors.

8. Strength and limitation

This study applies a structural equation modeling (SEM) approach, enabling the simultaneous examination of complex direct and indirect pathways. By integrating multiple domains, including socioeconomic, behavioral, biological, and environmental factors, the study provides a comprehensive understanding of depression. Furthermore, it contributes to the existing literature by highlighting key mediating mechanisms, particularly the central role of multimorbidity in linking these factors to depression.

However, this study has several limitations. The cross-sectional design restricts the ability to infer causal relationships between variables. In addition, potential confounding factors, such as cultural influences or unmeasured lifestyle variables, may not have been fully accounted for.

9. Future recommendations

Therefore, our study suggests that future research needs to adopt longitudinal designs to better establish causal relationships and temporal pathways between socioeconomic status (SES), multimorbidity, and depression. In addition, public health interventions need to prioritize multidimensional strategies, including promoting physical activity, preventing chronic diseases, and strengthening mental health services. Further research is also needed to explore regional disparities and cultural factors that may influence the relationship between social determinants and mental health.

AUTHOR CONTRIBUTIONS

Wahyu Tri Sudaryanto: Conceptualization, data analysis, and writing the original draft.
Wahyuni: Development of outcome measurement and critical revision of the original draft.
Firmansyah: Data curation, literature review, and manuscript editing.
Afif Ari Wibowo: Development of socioeconomic component measurement and contribution to the discussion on geographical potential risk factor dimensions.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest related to this study. The funding provided did not influence the study design, data collection, analysis, interpretation of the results, or the decision to publish the findings.

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