Research Article

Understanding Adolescent Suicide at the Population Level: The Role of Education, Inequality, and Health Indicators Across Nations

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ABSTRACT

Adolescent suicide is a leading cause of death among young people worldwide, yet limited research has explored how country level socioeconomic, technological, and health indicators collectively influence suicide rates. This study aimed to examine the associations between adolescent suicide rate (ASR) and multiple national level factors including income inequality, education, internet access, urbanization, and health-related behaviors. A cross-country analysis was based on publicly accessible data from the Global Burden of Disease Database and World Bank Databank. Pearson correlation models, multiple linear regression models and stepwise models were employed to determine significant predictors of suicide rates in adolescents in countries. Increased literacy and urban population proportions were uniformly related inversely to ASR, reflecting protective effects of education and urban infrastructure. Tobacco use had an unexpected inverse relationship with suicide rates, possibly due to confounding factors or cultural heterogeneity. GDP per capita was positively related to adolescent suicide, reflecting complicated interactions between economic condition and youth mental health. The findings suggest that higher literacy rate may serve as a protective factor in reducing adolescent suicide risk at the population level. Future research should explore individual-level data and cultural contexts to further clarify these associations and guide targeted interventions.

Keywords: Adolescent Suicide; Socioeconomic Determinants; Cross-national Analysis; Public Health; Literacy Rate

INTRODUCTION

Adolescent suicide has been a growing worldwide public health issue in recent decades with a rising rate of occurrence. Suicide is one of the principal causes of death in adolescents in every part of the globe (1). Although previous studies have investigated individual-level risk factors including mental disorder, drug use, and family maladjustment, relatively limited research has systematically examined how macro-level societal factors influence adolescent suicide at the population level.

A number of country-level factors have been suggested as having an impact on mental health outcomes, including socioeconomic disparity, access to education, health infrastructure, and internet access. Increased income

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inequality, as estimated using the GINI measure, has been postulated to lead to increased psychosocial strain and decreased mental health resource access (2). Alternatively, increased national wealth in terms of GDP per capita has been shown to correspond with increased health and educational services that can function as protective factors to mental health (3).

Another important factor that was considered was education. Especially literacy level and tertiary school enrollment has been linked to promoting resilience and coping strategies through knowledge, which can offset suicide risk (4). Urbanization has an ambivalent relationship in that while urban regions can have more mental health care available, they can also subject adolescents to higher social stress and disruption in social support systems (5). In addition, previous study has shown a higher risk of suicide in rural areas due to societal and socioeconomic reasons (6).

Also of interest is the rapid growth in internet access, and concerns regarding its dual potential as a source of social connection as well as its potential to aggravate social comparison and cyberbullying, contributing to increased psychological distress (7). Increased access to the internet also provides opportunities to self-growth through educational resources promoting intellectual development. However, at the same time, access to the internet poses a risk of exposure to uncontrolled information containing harmful content, such as self-harm and age-inappropriate sexual behaviors. These dual effects must be considered when interpreting its influence on adolescent suicide. Lastly, tobacco usage and body mass index (BMI) were considered to measure adolescent health as these variables have been previously documented correlations with mental health and general well-being (8).

In spite of increased awareness about youth suicide as an issue of public health, a lack of comprehensive cross-national studies exists on assessing general impacts of socioeconomic, educational, and behavioral variables. The study aimed to assess the major country-level socioeconomic, technological, and health factors that are linked with differences in rates of suicide among adolescents in different nations. Specifically, in this research, we examine higher literacy levels, increased urbanicity, reduced income inequality, increased access to the internet, and improved behavioral indicators such as reduced tobacco use and optimal body mass index, are linked to lower suicide rates among adolescents. By elucidating these potential population-level indicators, this research hopes to provide actionable data for devising targeted public health and policy interventions in reducing suicide among adolescents worldwide.

METHODS AND MATERIALS

Data Source and Variable Selection

Data for the study were collected from publicly accessible global datasets. Adolescent suicide rates (ASR) (10), GINI coefficient (a dimension of income inequality) (11), percentage of people living in urban population areas (12), gross domestic product per capita (13), literacy rate (% of people aged 15 years and older who can read and write) (14), and tertiary school enrollment rate (15) were collected from World Bank Open Data. Additional variables, such as fixed broadband internet subscription per 100 people, tobacco use rates, and mean body mass index (BMI), were obtained from the Global Burden of Disease Database hosted by the Institute for Health Metrics and Evaluation (16). The final dataset included 142 countries that were selected based on a data completeness criterion, wherein only those with at least 75% data availability across the key study variables were retained for inclusion. This ensured the reliability and representativeness of the global dataset while minimizing bias due to missing information.

This research sought to examine ASR as the main outcome measure due to its rising international prevalence and pressing public health interest (17). Socioeconomic factors were added in order to capture societal conditions that can affect mental health. Income inequality was measured using the GINI coefficient, which ranges from 0 (indicating perfect income equality) to 1 (indicating maximum inequality). A higher GINI score reflects a wider gap between the rich and the poor, and has been associated with increased psychosocial stress and limited access to mental health resources (18). GDP per capita was used as an indication of national prosperity and its resulting influence on infrastructure for care and education. Educational status was captured by literacy rate and tertiary school enrollment, which can indicate protective influences in relation to social mobility and cognitive resources (19). Urban population percentage was used to assess suicide risk differences between urban and rural settings. Technological exposure was measured in terms of broadband internet subscription rates per 100 individuals and internet use by a percentage of people, which captured potential effects of access to information and online engagement on mental wellbeing (20). Tobacco use rate and mean BMI were also included as indicators of behavioral and physical health since both have been previously illustrated to have dynamic relationships with psychological health in other studies (21). Following the assembly of this comprehensive dataset, statistical analyses were performed to evaluate the relationships between adolescent suicide rates and selected national indicators.

Statistical Analysis

All statistical analyses were conducted using GraphPad Prism (v10.1), Microsoft Excel (2024), and R version 4.3.2 in RStudio (2025 release). To explore the association between ASR and independent variables including internet usage and income inequality, Pearson correlation analysis was initially performed to identify the direction and strength of linear relationships (22). Multiple linear regression models were then employed to assess the combined and independent effects of predictors. All variables were entered into the regression model in their original units without standardization. As such, interpretation of β coefficients should consider the scale of each variable. Stepwise regression techniques were used to refine the model and identify the most parsimonious set of predictors (23).

RESULTS

The Pearson regression model analysis explored associations between ASR and a range of country-level variables, including year, socioeconomic indicators; GINI index (GINI), GDP per capita (GDP), and educational metrics; literacy rate (LIT), tertiary school enrollment (TSE), government expenditure on education (EOE), demographic factors; urban population percentage (UP), health-related measures; body mass index (BMI), tobacco use rate, and technological access indicators; fixed broadband subscriptions (FBIS) and individuals using the internet (IUI). Descriptive statistics for each variable are presented in Methods. Correlation and regression analyses were conducted to identify country-level factors significantly associated with ASR.

Data were analyzed from 142 countries included in the final dataset that retained 75% of the data for each variable that was of the study's interest. Data completeness was calculated based on the availability of yearly data from 2000 to 2016 on each of the 11 variables that were considered in this analysis. Out of 187 possible data entry during the scope of this research, only those countries containing over 140 entries were considered. Missing data was handled by listwise deletion; no imputation was performed.

Figure 1 presents a heat map of Pearson correlation coefficients between ASR and multiple country-level explanatory variables, including broadband internet access, GINI index (income inequality), government education spending, internet usage, tertiary school enrollment, urban population percentage, tobacco consumption, BMI, literacy rate, and GDP per capita. Correlation values range from -1 which reveals a perfect negative correlation, shown in dark red, to +1 denoting a perfect positive correlation, shown in dark blue. The matrix visually highlights key relationships, notably the strong negative association between ASR and literacy rate as well as a weak negative correlation with BMI, and positive correlation relationship among tertiary school enrollment rate.

Table 1 displays Pearson correlation coefficients between ASR and various country-level socioeconomic, educational, technological, and health indicators. Positive values represent direct relationships and negative values represent inverse relationships. All corresponding p-values of these correlations are listed separately in Table 2. Correlations must be interpreted in light of statistical significance thresholds described in Table 2.

Pearson correlation analysis revealed that ASR was significantly negatively associated with literacy rate and BMI, suggesting a potential protective effect of both education and physical health. In contrast, tertiary school enrollment showed a weak but statistically significant positive correlation with ASR. Other variables, including GDP per capita, income inequality (GINI), urban population percentage, tobacco use, internet access, and government education expenditure, did not demonstrate significant bivariate relationships with ASR (all $p > 0.05$). A complete list of Pearson correlation coefficients and their corresponding p-values is provided in Tables 1 and 2. Correlations were considered statistically significant at $p < 0.05$ but should be interpreted by considering both the strength of the association and the level of significance.

Table 3 displays the results of a multiple linear regression analysis assessing the relationship between ASR and a set of country-level explanatory variables. β coefficients represent the strength and direction of associations for each variable, with positive values indicating a direct relationship and negative values indicating an inverse relationship. P-values indicate the statistical significance of each predictor. Variables with $p < 0.05$ are considered statistically significant predictors of ASR in the full model.

A multiple linear regression model was created in order to explore the combined relationship between all

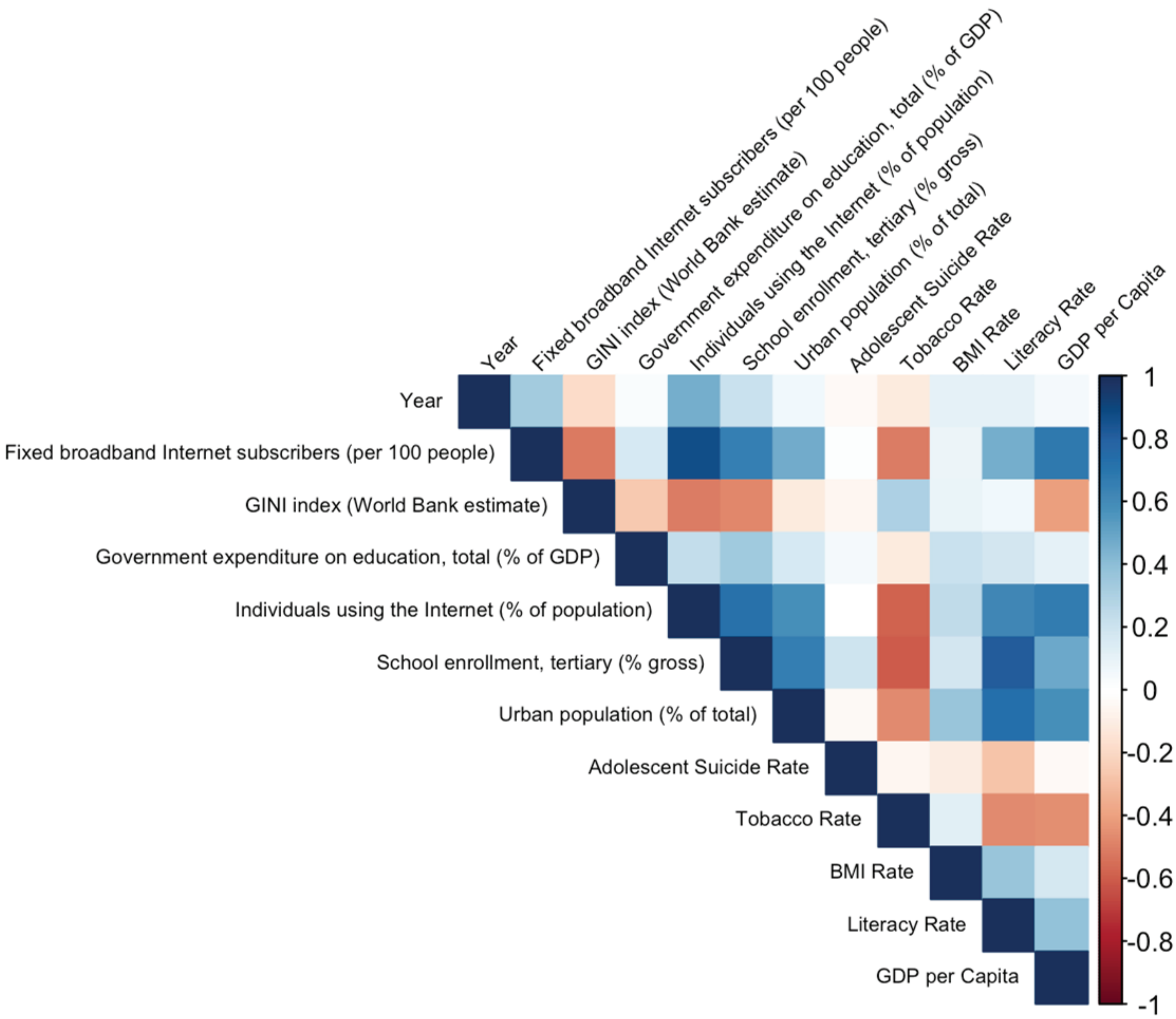

Figure 1. Correlation Matrix of ASR and Explanatory Variables. This Pearson correlation matrix depicted in the form of a heat map illustrates the correlation scores between ASR and various socioeconomic, demographic, and health indicators across countries. Strong positive correlations are shown in dark blue, strong negative correlations in dark red. Notable relationships such as the inverse correlation between ASR and literacy rate and the positive correlation with tertiary school enrollment were found.

Table 1. Pearson Correlation Coefficients Between ASR and Explanatory Variables

Variable	Year	ASR	FBIS	GINI	EOE	IUI	TSE	UP	Tobacco	BMI	LIT	GDP
Year	1.000	-0.036	0.332	-0.175	0.032	0.470	0.217	0.064	-0.116	0.119	0.112	0.059
ASR		1.000	0.015	-0.052	0.056	0.003	0.193	-0.040	-0.055	-0.108	-0.274	-0.038
FBIS			1.000	-0.480	0.169	0.874	0.650	0.476	-0.502	0.087	0.466	0.682
GINI				1.000	-0.245	-0.488	-0.443	-0.074	0.277	0.115	0.068	-0.377
EOE					1.000	0.238	0.342	0.166	-0.114	0.219	0.181	0.113
IUI						1.000	0.726	0.586	-0.584	0.250	0.630	0.678
TSE							1.000	0.669	-0.607	0.182	0.814	0.485
UP								1.000	-0.461	0.365	0.739	0.586
Tobacco									1.000	0.125	-0.469	-0.454
BMI										1.000	0.363	0.171
LIT											1.000	0.384
GDP												1.000

Table 2. Significance Levels for Correlation Between Suicide Rate and Study Variables

Variable	Year	ASR	FBIS	GINI	EOE	IUI	TSE	UP	Tobacco	BMI	LIT	GDP
Year	-	0.161	0.000	0.000	0.144	0.000	0.000	0.000	0.000	0.000	0.031	0.000
ASR		-	0.574	0.156	0.074	0.893	0.000	0.113	0.044	0.000	0.002	0.141
FBIS			-	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	-
GINI				-	0.000	0.000	0.000	0.016	0.000	0.001	0.440	0.000
EOE					-	0.000	0.000	0.000	0.000	0.000	0.007	0.000
IUI						-	-	-	0.000	0.000	0.000	-
TSE							-	-	0.000	0.000	0.000	0.000
UP								-	0.000	0.000	0.000	-
Tobacco									-	0.000	0.000	0.000
BMI										-	0.000	0.000
LIT											-	0.000
GDP												-

Table 3. Multiple Linear Regression Model Predicting ASR ($R^2 = 0.893$, F = 9.169, P < 0.001)

	Year	FBIS	GINI	EOE	IUI	TSE	UP	Tobacco	BMI	LIT	GDP
β Coefficient	0.874	0.773	-0.988	-0.904	-0.014	-1.242	-0.206*	-0.062*	-0.211	-1.001**	0.874*
P-value	0.137	0.815	0.729	0.299	0.490	0.868	0.047	0.012	0.324	0.002	0.049

explanatory variables and ASR by countries (Table 3). The model explained 89.3% of the variation in ASR ($R^2 = 0.893$, $F = 9.169$, $p < 0.001$). Literacy rate (β = -1.001, p = 0.002) was the strongest significant protective predictor among the predictors. Urban population percentage (β = -0.206, p = 0.047) and tobacco use (β = -0.062, p = 0.012) were also statistically significantly inversely related to teenage suicide rates. GDP per capita was significantly and positively associated with adolescent suicide rates (β = 0.874, p = 0.049), suggesting complex interactions between national prosperity and youth mental health. Other predictors, including broadband internet subscription, income inequality, education spending, and BMI, were not statistically significant in the full model (all $p > 0.05$). Full regression coefficients are presented in Table 3.

Table 4 presents the final stepwise multiple regression model identifying the most significant predictors of ASR from the full set of variables and eliminating residual effects of nonsignificant variables. The stepwise procedure was applied to improve model parsimony and reduce multicollinearity. β coefficients represent the direction and magnitude of the association between each predictor and ASR. Asterisks indicate levels of statistical significance (*p < 0.05, **p < 0.01). The final model explains 77.3% of the variance in ASR across countries.

Stepwise multiple regression was conducted in order to determine the most accurate and relevant group of predictors (Table 4). The final model accounted for 77.3% of the variability in ASR ($R^2 = 0.7726$, $F = 15.53$, $p < 0.000$). Strong predictors were literacy rate (β = -1.738, p = 0.000), which once more had the strongest protective effect, tobacco use (β = -0.176, p = 0.000), and percentage of urban population (β = -0.167, p = 0.002). GDP per capita had a slight but significant positive relationship (β = 0.001, p = 0.020), and the year of observation also had a significant upwards trend (β = 0.355, p = 0.013), as suicide rates in adolescents increased over time.

Government expenditure on education (β = −0.966, p = 0.062) and BMI (β = −0.345, p = 0.059) showed marginal relationships. All other variables were not included in the stepwise model based on a lack of statistical contribution to explaining the variances.

DISCUSSION

This research examined the relationship between ASR and a range of country-level socioeconomic, health and technological indicators. The best-fitting regression model explained a substantial proportion of variance in suicide rates, highlighting several key predictors that require closer interpretation.

Among all variables, literacy rate consistently demonstrated the strongest protective association with ASR. This finding highlight literacy as an essential buffer against psychological vulnerability in youth populations. Having a higher literacy rate may indicate not just access to formal education but also enhanced social mobility and access to mental health information. In contrast, tertiary school enrollment was initially positively associated with ASR, though this relationship did not remain in the later multiple regression model. This pattern may reflect academic pressures present in tertiary education systems; however, this interpretation remains speculative and may vary by cultural context. Urbanization also appeared to play a protective role, potentially due to greater access to mental health care, social services, or community infrastructure in urban areas. However, this relationship is likely to vary across countries depending on the quality of urban services and the presence of social support systems.

One of the more unexpected findings was the inverse association between tobacco use and ASR. While this may appear counterintuitive, prior literature suggests that in some cultural contexts, tobacco use may serve as a coping mechanism and a critical social activity that mitigates isolation or distress. For example, daily smoking among Chinese men is often perceived as a socially bonding behavior rather than purely a health risk (24). Nonetheless, these results must be interpreted with caution, as other studies have consistently linked tobacco use with poor mental health outcomes (25). This contradiction may reflect regional or cultural confounding factors and should not be taken to imply a causal protective effect. Another noteworthy and somewhat counterintuitive result was the positive relationship between GDP per capita and ASR. One possible explanation is that wealthier nations

Table 4. Stepwise Multiple Regression Model Predicting ASR ($R^2 = 0.7726$, $F = 15.53$, $P < 0.000$)

	Year	EOE	UP	Tobacco	BMI	LIT	GDP
β Coefficient	0.355*	-0.966	-0.167**	-0.176**	-0.345	-1.738**	0.001*
P-value	0.013	0.062	0.002	0.000	0.059	0.000	0.020

may have more robust suicide reporting systems, thereby inflating reported rates. Alternatively, economic growth may not equitably translate into improved access to mental health care for adolescents, especially in socially stratified societies.

Taken together, these findings emphasize the multifactorial nature of ASR and the complex interplay of structural, behavioral, and societal factors. While ecological studies cannot determine causality, they can help identify population-level trends that guide future research and intervention priorities.

CONCLUSION

This investigation offers significant findings in regard to the multifaceted and multicausal nature of suicide in adolescents worldwide. Through stepwise multiple linear analyses at the country level, we identified literacy rate as the most stable and potent protective factor against ASR, implying that access and achievement in education can significantly contribute to mitigating suicidality. Urban population percentage also yielded associations with decreased rates of suicide, while cigarette use revealed inverse relations warranting further investigation. Even though ecological design restricts causality, the results highlight the need for interventions considering structural and societal factors in mental health and global suicide prevention. Future studies involving individual level data and culturally focused regional findings are necessary for elucidating these relationships and developing targeted interventions in public health.

A number of limitations need to be taken into account when interpreting these findings. The analysis was undertaken for countries using aggregated data and thus cannot account for individual associations and risks of ecological fallacies. Second, data quality and availability varied per country and may have introduced bias or reduced the reliability of certain country-level indicators. Thirdly, some variables had results that defied expectation based on previous literature and are possibly due to unmeasured confounding variables or cultural and social determinants not captured in the analysis. Lastly, the study relied entirely on secondary data from global databases that may differ in measurement definitions, data collection methods, reporting quality, and completeness of data across different countries. Although efforts were made to match variables within the 2000–2016 window, some indicators may have originated from differing reporting years within that range, potentially introducing temporal mismatches that may have affected comparability across countries.

REFERENCES

1. World Health Organization. (2025, March 25). *Suicide*. World Health Organization. Available from: https://www.who.int/news-room/fact-sheets/detail/suicide (accessed on 2025-5-9)
2. Patel V, Burns JK, Dhingra M, Tarver L, et al. (2018). Income inequality and depression: A systematic review and meta-analysis of the association and a scoping review of mechanisms. *World Psychiatry*. 2018; 17 (1): 76–89. https://doi.org/10.1002/wps.20492
3. De la Escosura LP. Health, Income, and the Preston Curve: A Long View. *Economics & Human Biology*. 2022; 48: 101212. https://doi.org/10.1016/j.ehb.2022.101212
4. Minelli J, Jorge-Manuel Dueñas, Fàbia Morales-Vives & Gallardo-Nieto E. Educational agents and institutions called into action in suicide prevention, intervention, and postvention. *Frontiers in Psychology*. 2023; 14. https://doi.org/10.3389/fpsyg.2023.1213751
5. Srivastava K. Urbanization and mental health. *Industrial Psychiatry Journal*. 2009; 18 (2): 75–76. https://doi.org/10.4103/0972-6748.64028
6. Helbich M, Blüml V, de Jong T, Plener PL, et al. Urban–rural inequalities in suicide mortality: a comparison of urbanicity indicators. *International Journal of Health Geographics*. 2017; 16 (1). https://doi.org/10.1186/s12942-017-0112-x
7. Yu DJ, Yun Kwok Wing, Li T & Ngan Yin Chan. The Impact of Social Media Use on Sleep and Mental Health in Youth: a Scoping Review. *Current Psychiatry Reports*. 2024; 26 (3). https://doi.org/10.1007/s11920-024-01481-9
8. Peckham E, Lorimer B, Spanakis P, Heron P, et al. Health-risk behaviours among people with severe mental ill health: understanding modifiable risk in the Closing the Gap Health Study. *The British Journal of Psychiatry*. 2023; 222 (4): 1–7. https://doi.org/10.1192/bjp.2022.143
9. Institute for Health Metrics and Evaluation, University of Washington. (2021). *Global Burden of Disease (GBD).*
10. World Bank Group. (2024). *Global health indicator: Adolescent suicide rate*. Human Capital Data Portal. Available from: https://humancapital.worldbank.org/en/indicator/WB_HCP_SUICIDE_15_19?view=data+table (accessed on 2025-5-10)
11. World Bank Group. (2023). *Global Health Indicator: GINI Index*. World Bank Databank. Available from: https://data.worldbank.org/indicator/SI.POV.GINI (accessed on 2025-5-9)
12. World Bank Group. (2023). *Global Health Indicator: Urban population (% of total)*. World Bank Databank. Available from: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS (accessed on 2025-5-11)
13. World Bank Group. (2025). *Global Health Indicator: GDP per capita (current US$)*. World Bank Databank. Available

from: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD (accessed on 2025-5-11)

14. World Bank Group. (2025). *Literacy rate, youth total (% of people ages 15-24*). World Bank Databank. Available from: https://data.worldbank.org/indicator/SE.ADT.1524.LT.ZS (accessed on 2025-5-11)
15. World Bank Group. (2024). *School enrollment, Tertiary (% gross)* World Bank Databank. Available from: https://data.worldbank.org/indicator/SE.TER.ENRR (accessed on 2025-5-11)
16. Institute for Health Metrics and Evaluation. Available from: https://vizhub.healthdata.org/gbd-results (accessed on 2025-5-8)
17. Bertuccio P, Amerio A, Grande E, Carlo La Vecchia, et al. Global trends in youth suicide from 1990 to 2020: an analysis of data from the WHO mortality database. *EClinicalMedicine*. 2024; *70*: 102506–102506. https://doi.org/10.1016/j.eclinm.2024.102506
18. Kåks P, Målqvist M, Forsberg H & Fjellborg AA. Neighborhood income inequality, maternal relative deprivation and neonatal health in Sweden: A cross-sectional study using individually defined multi-scale contexts. *SSM - Population Health*. 2025; 29: 101745. https://doi.org/10.1016/j.ssmph.2024.101745
19. Lövdén M, Fratiglioni L, Glymour MM, Lindenberger U & Tucker-Drob EM. Education and Cognitive Functioning Across the Life Span. *Psychological Science in the Public Interest*. 2020; 21 (1): 6–41. https://doi.org/10.1177/1529100620920576
20. Yu J & Meng S. Impacts of the Internet on Health Inequality and Healthcare Access: a Cross-Country Study. *Frontiers in Public Health*. 2022; 10 (935608). https://doi.org/10.3389/fpubh.2022.935608
21. National Center for Chronic Disease Prevention and Health Promotion (US) Office on Smoking and Health. (2012). *The Health Consequences of Tobacco Use Among Young People*. Nih.gov; Centers for Disease Control and Prevention (US). https://www.ncbi.nlm.nih.gov/books/NBK99242/
22. Schober P, Boer C & Schwarte LA. Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Analgesia*. 2018; 126 (5): 1763–1768. https://doi.org/10.1213/ANE.0000000000002864
23. Fritz M & Berger PD. Can you relate in multiple ways? Multiple linear regression and stepwise regression. *Elsevier EBooks*. 2015: 239–269. https://doi.org/10.1016/b978-0-12-800635-1.00010-0
24. Huang X, Fu W, Zhang H, Li H, et al. Why are male Chinese smokers unwilling to quit? A multicentre cross-sectional study on smoking rationalisation and intention to quit. *BMJ Open*. 2019; 9 (2): e025285. https://doi.org/10.1136/bmjopen-2018-025285
25. Prochaska JJ, Das S & Young-Wolff KC. Smoking, Mental Illness, and Public Health. *Annual Review of Public Health*. 2017; 38 (1): 165–185. https://doi.org/10.1146/annurev-publhealth-031816-044618