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Urbanization and the Network Role of Loneliness in Adolescent Suicide Risk: A Four-Stage Analysis Across 87 Countries

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Research Article

Keywords: adolescent suicide, network analysis, urbanization, cross-cultural comparison, loneliness, GSHS

Posted Date: March 23rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9083788/v1

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Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at European Child & Adolescent Psychiatry on October 27th, 2026. See the published version at https://doi.org/10.1007/s00787-026-03233-x.

Abstract

Background

The loneliness–suicide association has been confirmed across countries, but what macro-level conditions account for cross-national variation in its strength remains unknown.

Methods

Four-stage analysis of 439,026 adolescents (13–17 years; 52.1% female) from 87 countries in five non-European WHO regions using GSHS data. Stage 1: psychometric networks (EBICglasso) with regional centrality comparisons. Stage 2: cross-regional XGBoost transfer with SHAP feature importance. Stage 3: ecological correlations between 11 macro-indicators and SHAP profiles (*N* = 42 countries), with GLMM and specification curve analysis. Stage 4: urbanization–edge weight associations across 38 country-specific networks.

Results

Suicidal ideation ranked in the top two by Strength centrality across all WHO regions (Stage 1). Prediction models failed to transfer across regions (mean AUC degradation = 17.3 percentage points), with loneliness as the most variable predictor (Stage 2). Urbanization showed the strongest association with loneliness SHAP importance (*r*_s = .655, *p*_FDR = .0003, *N* = 42); a GLMM confirmed this at the individual level (OR = 1.096, 95% CI [1.053, 1.140], *p* = 6.2 x 10^-6), with 94.4% of 432 specification curve variants yielding *p* < .05 (Stage 3). Urbanization was positively correlated with the loneliness–suicidal ideation edge weight (*r*_s = + .639, *p*_FDR < .001) and negatively with the friendship–loneliness edge weight (*r*_s = − .799, *p*_FDR < .0001; Stage 4).

Conclusions

The network role of loneliness in adolescent suicide risk varies with national urbanization level: in higher-urbanization contexts, loneliness's risk connections strengthen while protective connections weaken. If confirmed longitudinally, these patterns would support development-stage-adapted prevention over uniform global templates.

Introduction

Suicide claimed 727,000 lives globally in 2021 and remains the third leading cause of death among 15–29-year-olds [1]. Although the age-standardized suicide rate declined from 14.9 to 9.0 per 100,000 between 1990 and 2021 [41], the trajectory among adolescents is heterogeneous: global suicide mortality among 10–24-year-olds decreased overall, but regional and sociodemographic disparities

widened substantially [42]. Multiple high-income countries have reported rising adolescent suicidal ideation and self-harm [2, 3], while LMICs remain underrepresented in the evidence base [4]. The WHO Global School-based Student Health Survey (GSHS) is one of the largest adolescent health databases and allows large-scale cross-cultural comparison [5, 44]. GSHS microdata are publicly released with a lag following data collection, and country participation is staggered across survey cycles [44]; combined with school closures during the COVID-19 pandemic (2020–2021), this means the 158 datasets spanning 2003–2017 used in the present study represent the most comprehensive publicly available GSHS resource at the time of analysis.

The Network Approach

Traditional risk factor research adopts a variable-centered perspective, treating each predictor as an independent contributor. However, the comorbidity and multifactorial nature of mental health problems suggest that interactions among risk factors—rather than isolated effects of individual factors—may better capture pathological mechanisms [6]. Psychometric network analysis models symptoms and risk factors as network nodes and their conditional dependencies as edges. Central nodes—variables with the greatest influence on overall network structure—and cross-domain bridge nodes that connect different symptom clusters can then be identified [6–9]. This approach is now widely applied in clinical psychology [7, 9] but remains scarce in large-scale cross-cultural studies of adolescent suicide.

Gaps in the Literature

Existing cross-cultural analyses using GSHS data leave three questions unanswered. First, although large-scale cross-cultural descriptions exist—Campisi et al. [10] conducted a pooled analysis of GSHS data from 90 countries and compared suicide behavior prevalence by income group, finding no significant differences—few studies have tested national-level moderating effects. Abio et al. [11] tested interactions between macro-level indicators (GDP, Gini coefficient, population density) and individual risk factors using multilevel logistic regression in GSHS data from 53 LMICs (with interaction tests conducted in a 33-country analytic subset), but none of the interaction terms reached significance, and urbanization rate was not among the indicators tested. A wider cross-national range may be needed to detect these associations, and alternative analytic approaches may complement the multilevel interaction framework.

Second, Hu et al. [12] applied country-specific logistic regressions followed by random-effects meta-analysis to GSHS data from 93 countries, establishing that the loneliness–suicidal behavior association is present in the vast majority of countries (overall OR = 2.41 for suicidal ideation). This confirmation of cross-cultural universality provides a foundation for a complementary question: given that the association exists nearly everywhere, what macro-level conditions are associated with cross-national variation in its strength? Third, Freije et al. [13] tracked temporal trends in adolescent loneliness across 38 OECD countries but did not examine urbanization as an explanatory variable.

Building on this established universality [12], the present study took a different analytical approach—psychometric network analysis—for two reasons. First, a network framework models all risk and protective factors as simultaneously interacting nodes rather than separating them into a single predictor and a set of covariates; this makes it possible to examine the *structural role* of loneliness (e.g., its centrality, its bridge position between protective and risk domains, and the specific edges connecting it to other nodes) within the broader system. Second, once these structural features are quantified at the country level, they can be linked to macro-level indicators to ask not just *whether* loneliness is associated with suicidal behavior, but *under what societal conditions* loneliness plays a stronger or weaker role in the network—a question that requires edge-level and node-level variation across countries as input.

The Present Research

This study adopted a four-stage progressive design. All four studies analyzed the same GSHS dataset from complementary analytical perspectives—node-level (Stage 1), model-level (Stage 2), macro-micro ecological (Stage 3), and edge-level (Stage 4)—and their consistency reflects analytic convergence, not independent replication (see Discussion). The pipeline was developed iteratively; the focus on loneliness and urbanization emerged from data-driven screening in Stages 2–3 rather than from prior hypotheses (see Declarations: Preregistration).

1. Stage 1 estimated global and regional psychometric networks and tested the cross-cultural consistency of central nodes.
2. Stage 2 tested the cultural heterogeneity of prediction pathways through cross-regional model transfer experiments and identified sources of variation.
3. Stage 3 tested associations between macro-indicators such as urbanization and the risk role of loneliness at the country level (N = 42), with robustness checks via individual-level multilevel modeling and specification curve analysis.
4. Stage 4 tested associations between urbanization rate and specific network edge weights across 38 countries.

Stage 1: Global Risk Network and Cross-Cultural Consistency

Methods

This study is reported following STROBE guidelines for cross-sectional studies [14]. A completed STROBE checklist is provided in the Supplemental Materials.

Participants and Data

Data came from the WHO Global School-based Student Health Survey (GSHS), which employs two-stage cluster sampling to select nationally representative schools and classes, covering in-school adolescents aged 13–17. We downloaded all 158 available datasets (100% acquisition rate; survey years spanning

2003–2017) from the WHO public database, yielding a combined sample of 439,026 adolescents from 87 countries across five WHO regions (Americas, Africa, Eastern Mediterranean, South-East Asia, Western Pacific). The GSHS does not cover the European region (European adolescent health data are collected separately by the WHO-Europe Health Behaviour in School-Aged Children [HBSC] survey), and thus no European countries were included. This dataset was shared across all four stages; subsequent stages describe only their stage-specific analytic samples and methods. Of the total sample, 52.1% were female and 46.9% male (0.9% missing); the modal age categories were 14 (22.7%) and 15 (22.0%), with 88.8% in the 13–17 target range. Overall prevalence rates were 17.7% for suicidal ideation, 14.9% for suicide plan, and 20.9% for suicide attempt (at least once). Regional sample sizes ranged from 50,479 (Eastern Mediterranean, 12 countries) to 160,457 (Americas, 29 countries); complete country-level demographic information is provided in Table S1.

Measures

Network analysis used 15 node variables: three suicidal behavior variables (suicidal ideation, suicide plan, suicide attempt), three mental health variables (loneliness, worry-induced insomnia, number of close friends), four protective factors (peer support, parental understanding, parental monitoring, parental homework involvement), and five risk factors (hunger, physical attack, physical fight, insufficient physical activity, truancy). Suicidal ideation and suicide plan were binary variables (yes/no); the remaining 13 variables were ordinal (ranging from 2 to 8 categories; e.g., loneliness ranged from “never” to “always” on a 5-point scale; physical attack ranged from 0 to 12 + times on an 8-point scale). All variables were entered in their original ordinal coding into a polychoric correlation matrix, which appropriately handles mixtures of ordinal and binary data. Close friends is both a mental health indicator and a protective factor; the GSHS questionnaire groups it with psychosocial distress items (loneliness, worry-insomnia, close friends) in the Mental Health Core module rather than with family/peer support items, so it was classified accordingly, though its association with loneliness was interpreted as a protective connection in the results. Complete cases (no missing data across all 15 variables) totaled 292,280 individuals.

Network Estimation and Comparison

The global network was estimated using the EBICglasso method (*N* = 292,280 [15]) based on a polychoric correlation matrix. The EBIC hyperparameter was set to gamma = 0.5 to promote sparse solutions. Because the 15 variables were drawn from distinct GSHS modules (suicidal behavior, psychosocial distress, family environment, violence, and health behavior), the Goldbricker test [35] confirmed no topologically overlapping node pairs, indicating that all variables contributed unique information to the network. Subnetworks were estimated separately for each of the five WHO regions. The centrality metric was node Strength.

Between-region network comparisons used the Network Comparison Test (NCT [16]). For each pairwise comparison, 5,000 individuals were randomly sampled from each region (the computational complexity

of NCT's permutation test is O(*n*^2 x *iterations*), making full-sample analysis infeasible; *n* = 5,000 ensures sufficient convergence of EBICglasso partial correlation estimates). To assess sensitivity to the random subsample, we repeated the procedure across three independent draws; the pattern of significant comparisons was identical across draws. Global strength differences were assessed via 1,000 permutation tests, with *p*-values corrected using the Benjamini-Hochberg FDR procedure (10 pairwise comparisons [17]). Bootstrap stability analysis (2,500 resamples) computed the CS-coefficient to assess the stability of centrality rankings. All analyses were conducted in R (version 4.3) using the bootnet (v1.5), qgraph (v1.9), and NetworkComparisonTest (v2.2.2) packages.

Results

The EBICglasso network (15 nodes, *N* = 292,280 complete cases; Fig. 1) was consistent with the loneliness–suicidal behavior association established by Hu et al. [12]: descriptive prevalence rates closely matched their weighted estimates (e.g., frequent loneliness: 13.5% vs. 13.2%; regional rank order identical). The network approach complemented this established association by revealing the multivariate conditional dependency structure among all 15 variables simultaneously.

Suicidal ideation had the highest Strength centrality (1.257), followed by suicide attempt (1.091) and suicide plan (1.005). Loneliness ranked sixth (Strength = 0.831) but occupied a bridge-like position connecting the mental health and protective factor domains (cf. [18]). The strongest edge was suicidal ideation–suicide plan (weight = 0.588), followed by parental monitoring–parental homework involvement (0.370) and loneliness–worry-induced insomnia (0.362). The network contained 31 negative edges, primarily between protective factors (e.g., close friends, peer support) and risk/distress nodes, revealing a signed dependency structure across risk and protective domains.

Expected Influence (EI) rankings were consistent with Strength rankings (r_s = .789, p < .001; top three identical), as expected given that both indices derive from the same adjacency matrix; this convergence confirms the dominance of positive edges in the network. Node predictability (mixed graphical models [36]) yielded mean R^2 = .19; suicidal ideation was highest (.35) and physical activity lowest (.04). Full indices are in Table S2.

Figure 1 Global adolescent mental health risk network (EBICglasso, *N* = 292,280, 87 countries). Vermillion = mental health, bluish green = protective factors, sky blue = risk factors. Node size proportional to Strength centrality; edge width proportional to partial correlation weight (blue = positive, vermillion dashed = negative). Abbreviations: SI = suicidal ideation, SP = suicide plan, SA = suicide attempt, Lon = loneliness, Wry = worry-insomnia, Frd = close friends, PeS = peer support, PaU = parental understanding, PaM = parental monitoring, PaH = parental homework, Hng = hunger, Atk = physical attack, Fgt = physical fight, PhA = physical activity, Trc = truancy.

Suicidal ideation ranked in the top two by Strength across all five regional subnetworks (range: 1.09–1.32; first in the Americas and Eastern Mediterranean; second elsewhere). NCT indicated partial regional

differentiation: 4 of 10 pairwise comparisons reached significance after FDR correction (full results in Table S4). Loneliness Strength varied modestly across regions (Americas: 0.992; Eastern Mediterranean: 0.969; South-East Asia: 0.722; Africa: 0.705; Western Pacific: 0.715), but Stage 2 would show more pronounced variation through SHAP importance. Bootstrap stability analysis confirmed reliable centrality rankings (CS-coefficient = 0.75, above the 0.50 threshold; see Supplemental Fig. S2).

Stage 2: Cross-Regional Model Transfer

Method

Using the same GSHS dataset, we trained XGBoost binary classifiers (12 non-suicide features predicting suicidal ideation) separately within each WHO region. Model hyperparameters were set to *n*_estimators = 300, max_depth = 6, learning_rate = 0.1, subsample = 0.8, and colsample_bytree = 0.8. Class imbalance was addressed via scale_pos_weight = *n*_negative/*n*_positive (overall ratio approximately 4.65, given SI prevalence of 17.7%; computed separately for each region). Model performance was evaluated via stratified 5-fold cross-validation within each region and cross-region transfer, with AUC as the primary performance metric (F1-scores showed a consistent degradation pattern and are reported in Table S5). A 5 x 5 transfer matrix (training region x test region) was constructed.

For each country with *N* > = 2,000 (42 countries), we used SHapley Additive exPlanations (SHAP [19]) to extract 12-dimensional feature importance vectors and computed cross-regional coefficients of variation to identify the most culturally sensitive predictors. Because SHAP values sum to the model's prediction for each observation, an increase in one feature's SHAP importance mechanically reduces the remaining features' share; the ecological correlations in Stage 3 should be interpreted with this compositional constraint in mind (see Limitations). Analyses were conducted in Python (version 3.10) using the xgboost (v1.7) and shap (v0.42) libraries.

Results

Models failed to transfer: within-region mean AUC was 0.868, cross-region mean AUC was 0.695, representing an average degradation of 17.3 percentage points (Fig. 2). The South-East Asia model performed best within its own region (AUC = 0.921) but dropped to 0.625 when transferred to Africa.

Figure 2 Cross-regional model transfer matrix. Diagonal = within-region AUC (mean = 0.868); off-diagonal = cross-region AUC (mean = 0.695). Mean degradation of 17.3 percentage points. Amer = Americas, Afr = Africa, EMed = Eastern Mediterranean, SEA = South-East Asia, WPac = Western Pacific.

To localize the sources of non-transferability, we computed cross-regional SHAP importance coefficients of variation for each predictor. The three most variable predictors were loneliness (CV = 0.386), hunger (0.352), and parental understanding (0.346). These CV values were closely comparable (spread of 0.040), meaning Stage 2 alone could not distinguish loneliness as the primary source of variation. Stage 3 would systematically test all 12 predictors' associations with 11 macro-level indicators (132 tests

total); the selection of loneliness as the focal variable was based on the results of that systematic test rather than on the CV rankings from Stage 2. The high CV values indicate that these predictors play different predictive roles across regions, constituting the primary sources of cross-regional transfer degradation.

Stage 3: Urbanization and the Risk Role of Loneliness

Method

Macro-Level Indicators

Country-level indicators included seven World Bank variables (GDP per capita, Gini coefficient, urbanization rate, internet penetration, health expenditure as percentage of GDP, life expectancy, suicide rate) and four Hofstede cultural dimensions (individualism, power distance, uncertainty avoidance, masculinity). For each country, World Bank indicators were matched to the median survey year of that country's GSHS data (e.g., if a country's surveys spanned 2007–2013, the 2010 World Bank values were used); Hofstede dimensions, which are treated as stable cultural parameters, were taken from the most recent available estimates.

Ecological Correlations

Spearman correlations were computed between each country's 12-dimensional SHAP vector (from Stage 2) and 11 macro-level indicators across 42 countries (sample size > = 2,000), with Benjamini-Hochberg FDR correction (132 tests). Ninety-five percent confidence intervals for the strongest correlations were estimated via percentile bootstrap (10,000 resamples).

Individual-Level GLMM

As a complementary analytic approach, we used a generalized linear mixed model (GLMM) to test the same association at the individual level. Because the GLMM and SHAP analyses both used the same GSHS data (at different levels of aggregation), their consistency should be interpreted as analytic convergence rather than independent sample validation [20, 21]. We fitted a logistic random-slopes model:

suicidal_ideation ~ loneliness + worry_insomnia + … + urbanization_pct + loneliness:urbanization_pct + age + sex + (1 + loneliness | country)

where urbanization rate was globally z-standardized (M = 0, SD = 1), age was grand-mean centered, and 12 individual-level binary predictors were entered in original 0/1 coding. Group-mean centering was not applied because the binary predictors have a natural zero point and the random slope for loneliness already captures between-country variation in the loneliness–SI association; centering would alter the

cross-level interaction semantics without improving interpretability [37]. The loneliness x urbanization_pct interaction was the key term; only this interaction was included because the ecological screening in Stage 3 (132 FDR-corrected tests across all 12 predictors x 11 indicators) had already identified urbanization–loneliness as the strongest macro-micro association, and the GLMM served as a focused individual-level test of that specific result rather than a discovery step. *N* = 296,863 individuals nested within 42 countries. Model comparison used likelihood ratio tests. The GLMM was fitted in R using lme4 [22] with the bobyqa optimizer (maxfun = 200,000); the model converged without warnings.

Specification Curve Analysis

Specification Curve Analysis (SCA [23]) systematically varied five analytic dimensions: outcome variable (suicidal ideation/plan/attempt), feature subset (all 12/drop weakest 3/top 5/top 3), control variables (none/+age/+age + sex/+age + sex+grade), estimation method (cluster-robust logistic/LMM/GLMM), and country inclusion threshold (*N* > = 2,000/1,000/500), generating 432 specifications. The direction, significance, and effect size of the loneliness x urbanization interaction were reported for each specification.

Results

Ecological Correlations

Among 132 macro-micro associations, the urbanization–loneliness SHAP correlation was strongest (*r*_s = .655, 95% CI [.41, .81], *p*_FDR = .0003, *N* = 42; Fig. 3). Two methodological caveats apply to interpreting these ecological correlations. First, because ecological correlations are inflated by aggregation [24], the individual-level GLMM interaction (OR = 1.096; see below) should be treated as the primary effect size estimate; the ecological *r*_s = .655 describes the country-level pattern but overstates the individual-level effect. Second, because SHAP values are compositional (they sum to the model's prediction for each observation), an increase in one feature's importance mechanically constrains others; the negative correlations reported below (e.g., close friends, hunger) may partly reflect this zero-sum property rather than genuine reductions in those features' predictive roles. Stage 4's edge-weight analysis, which does not share this compositional constraint, provides the critical non-compositional check (see Stage 4 Results).

Seven associations survived FDR correction (Table 1): urbanization and internet penetration were positively correlated with loneliness and worry-insomnia SHAP importance (*r*_s = .466–.655), while urbanization was negatively correlated with close friends SHAP importance (*r*_s = − .545).

Table
1
FDR-Significant Macro-Micro Associations (Stage 3)

Macro indicator	SHAP feature	*r_s*	*p_FDR*	*N*
Urbanization rate	Loneliness	+ .655	.0003	42
Urbanization rate	Close friends	− .545	.009	42
Internet penetration	Loneliness	+ .542	.009	42
GDP per capita	Worry-insomnia	+ .542	.010	40
GDP per capita	Loneliness	+ .515	.018	40
Internet penetration	Worry-insomnia	+ .466	.036	42
Uncertainty avoidance[a]	Loneliness	+ .591	.036	25

Note

Spearman correlations between country-level macro indicators and SHAP feature importance for suicidal ideation prediction. Only 7 of 132 tests survived Benjamini-Hochberg FDR correction ($p < .05$). All World Bank indicators: $N = 40–42$. [a] Hofstede cultural dimension; only 25 countries had data (95% CI [.22, .82]). This result should be interpreted with caution given the smaller sample and wider confidence interval.

The pattern is consistent with a gradient in which survival-level threats such as hunger and violence carry greater relative weight in suicide risk prediction in low-urbanization countries, while psychosocial factors such as loneliness and worry-induced insomnia gain relative weight in higher-urbanization countries. That only 7 of 132 tests survived FDR correction indicates that the macro-level context is not associated with all risk factors' roles but selectively linked to the specific loneliness/worry-insomnia pathway.

Figure 3 Key macro-micro associations. (a) Urbanization vs. loneliness SHAP (*r_s* = .655, *p_FDR* = .0003). (b) Urbanization vs. close friends SHAP (*r_s* = − .545, *p_FDR* = .009). (c) Internet penetration vs. loneliness SHAP (*r_s* = .542, *p_FDR* = .009). (d) GDP per capita vs. worry-insomnia SHAP (*r_s* = .542, *p_FDR* = .010). Points colored by WHO region.

Individual-Level GLMM

To test the same association at the individual level (using the same data at a different aggregation level, not an independent sample [25]), we fitted an individual-level GLMM ($N = 296{,}863$ in 42 countries). The interaction term yielded OR = 1.096 (95% CI [1.053, 1.140], $p = 6.2 \times 10^{-6}$): in countries one standard deviation higher in urbanization, the loneliness–suicidal ideation association was approximately 9.6% stronger. The random-slopes model was superior to random-intercepts ($\chi^2 = 481.51$, $df = 2$, $p < 2.2 \times 10^{-16}$; null-model ICC = .073). Full random effects are in Table S8.

Specification Curve Analysis

Among 432 specification variants (3 outcome variables x 4 feature subsets x 4 covariate sets x 3 estimation methods x 3 country thresholds), the loneliness x urbanization interaction yielded $p < .05$ in 94.4% (408/432) and was positive in 100% (432/432; Fig. S10).

The 432 specifications are not independent, so the 94.4% rate is a descriptive consistency indicator. Without the permutation-based *p*-curve test recommended by Simonsohn et al. [23], which was computationally prohibitive for 432 multilevel models, SCA results here serve as a sensitivity analysis rather than confirmatory inference (see Supplemental Materials for rationale). Stratified by outcome: 100% of specifications with suicidal ideation and suicide plan were significant, but only 83.3% of suicide attempt specifications reached significance, suggesting that the urbanization–loneliness interaction is more robustly associated with cognitive/ideation-stage outcomes than with behavioral outcomes. This dissociation is consistent with ideation-to-action frameworks [26], which posit that additional factors (e.g., impulsivity, capability for suicide, means availability) govern the transition from ideation to attempt, and suggests that the urbanization–loneliness pathway primarily operates at the ideation stage. The median interaction coefficient was OR = 1.106 (range: 1.031–1.198; limited to the 288 logistic model specifications; the 144 LMM specifications yielded linear coefficients on a different scale and were not included in the OR summary).

Robustness Checks

In addition to the GLMM and SCA reported above, we conducted several supplementary robustness checks (Fig. S11; see Supplemental Materials for full details).

Partial Correlation Control. After controlling for GDP per capita and internet penetration, the partial Spearman correlation between urbanization rate and loneliness SHAP importance remained significant ($r_{s,partial} = .466$, $p = .003$), a 29% attenuation from the zero-order $r_s = .655$. This attenuation indicates that a meaningful portion of the urbanization–loneliness association is shared with economic development and digitalization, but the residual association after partialling out these indicators suggests that urbanization captures additional variance beyond GDP and internet penetration alone.

SHAP Stability. Across five random seeds, the mean Spearman correlation among countries' SHAP vectors was .919, and the urbanization–loneliness correlation ranged from .586 to .676, consistently significant.

Leave-One-Out. Sequentially removing any single country from the 42-country sample, the urbanization–loneliness SHAP correlation remained significant in all iterations. No single country drove the results.

Missing Data. The suicidal ideation-specific missing rate was not correlated with urbanization rate ($r_s = -.150$, $p = .343$). However, the overall missing rate (proportion with any of 15 variables missing) was significantly negatively correlated with urbanization rate ($r_s = -.454$, $p = .003$), meaning lower-urbanization countries had higher overall missingness. Complete-case analysis may therefore introduce greater selection bias in lower-urbanization countries, a limitation discussed further below.

Survey Weight Sensitivity. A weighted GLMM using normalized GSHS sampling weights yielded OR = 1.085 (95% CI [1.041, 1.131], p = 1.10 x 10^-4), with negligible weighted-unweighted difference (delta-OR < .005).

Survey Year. Survey year was uncorrelated with urbanization (r_s = .175, p = .269). Adding survey year as a covariate changed the interaction negligibly (delta-OR = .001). A loneliness x survey year interaction indicated that the loneliness–SI association has strengthened over time (OR_year = 1.017, p < .001), but the urbanization interaction remained unchanged.

Multiple Survey Waves. Restricting to each country's most recent wave only (N = 216,692, 39 countries) yielded OR = 1.081 (95% CI [1.033, 1.132], p = 8.9 x 10^-4), confirming that wave pooling did not inflate the association.

Because SHAP is an aggregate node-level indicator that cannot distinguish which specific edges of loneliness are affected, Stage 4 examined this question at the edge level.

Stage 4: Urbanization and Network Edge Weight Association Patterns

Method

In 38 countries with complete 15-variable data and N > = 500 (36 overlapping with Stage 3), country-specific regularized partial correlation networks were estimated using GraphicalLassoCV (sklearn, Python), which selects the regularization parameter via cross-validation and provides greater stability for batch estimation across many countries than EBICglasso. The lower sample size threshold (N > = 500 vs. Stage 3's N > = 2,000) was used because edge-weight estimation is less parameter-intensive than SHAP profiling; sensitivity analysis restricting to N > = 2,000 yielded the same pattern of significant edges. Both are L1-regularized Gaussian graphical models; GraphicalLassoCV uses Pearson rather than polychoric correlations, which may attenuate absolute edge weights but preserves cross-national rankings (the focus of Stage 4) as long as attenuation is approximately uniform. Country-level prevalence rates of loneliness and suicidal ideation were not correlated with urbanization (loneliness: r_s = − .199, p = .073; SI: r_s = .038, p = .741), indicating that differential base-rate attenuation of Pearson correlations was unlikely to produce spurious cross-national associations. The Pearson-polychoric distinction affects absolute edge magnitudes but not the cross-national ranking of edge weights, which is the quantity correlated with urbanization in Stage 4. The convergence between Stage 3 (EBICglasso/polychoric, SHAP) and Stage 4 (GraphicalLassoCV/Pearson, edge weights) should be interpreted with the caveat that both the estimation method and correlation type differ across stages.

We extracted 15 x 14 / 2 = 105 unique edge weights and computed Spearman correlations between each edge weight and national urbanization rate, with Benjamini-Hochberg FDR correction (105 tests). Association patterns were analyzed by edge domain classification.

Results

Seventeen of 105 edges (16.2%) survived FDR correction (Fig. 4; Table 2), revealing a consistent pattern.

Table
2

FDR-Significant Urbanization–Edge Weight Associations (Top 9 of 17; Stage 4)

Edge	*r_s*	*p_FDR*	Direction
Loneliness – Close friends	− .799	< .0001	Protection weakened
Loneliness – Suicidal ideation	+ .639	.0008	Risk strengthened
Peer support – Physical attack	− .611	.0013	Buffer weakened
Loneliness – Parental monitoring	− .609	.0013	Protection weakened
Physical fight – Physical activity	+ .592	.0019	Strengthened
Worry-insomnia – Physical fight	− .585	.0020	Weakened
Loneliness – Peer support	− .543	.0065	Protection weakened
Parental homework – Physical fight	− .533	.0073	Buffer weakened
Peer support – Hunger	− .530	.0073	Buffer weakened

Note

Spearman correlations between country-specific edge weights (GraphicalLassoCV partial correlations, *N* = 38 countries) and national urbanization rate. Top 9 of 17 FDR-significant edges shown; full results in Table S10.

Among the 17 FDR-significant edges, 12 were negative (protective/buffering edges weaker in higher-urbanization countries) and 5 were positive (risk edges stronger). Edges spanning Mental Health and Protective Factor domains showed the strongest urbanization associations (mean |*r*_s| = .348; 5 of 12 FDR-significant).

In higher-urbanization countries, loneliness was subject to compounding structural disadvantages: a stronger direct association with suicidal ideation (*r*_s = + .639) and weaker buffering from friendship (*r*_s = − .799), parental monitoring (*r*_s = − .609), and peer support (*r*_s = − .543)—consistent with Stage 3's SHAP findings. Because edge weights are not subject to the compositional (zero-sum) constraint that affects SHAP values, these results provide a non-compositional confirmation of the Stage 3 pattern. These associations are based on cross-national comparisons and do not support causal inference. Fig. S12 presents a network-level visualization of this rewiring pattern, with FDR-significant edges colored by direction (red = strengthened, blue = weakened in higher-urbanization countries).

Figure 4

Discussion

Summary of Findings

Four-stage network analysis of 439,026 adolescents across 87 countries yielded associational evidence at the node level (centrality), model level (SHAP importance), ecological level (country-level correlations), and edge level (partial correlations). Suicidal ideation consistently occupied a central position in the risk network across all cultural contexts (Stage 1: global Strength rank first, top two in all regions), but specific pathways predicting suicidal ideation failed to transfer across regions (Stage 2: AUC degradation of 17.3 percentage points), with loneliness as the most variable predictor. Among 11 macro-level indicators tested, urbanization rate showed the strongest association with this variation (Stage 3: *r*_s = .655); an individual-level multilevel model on the same data provided directionally consistent cross-level evidence (OR = 1.096, *p* = 6.2 x 10^-6), with 94.4% of 432 analytic specifications yielding *p* < .05. At the edge level, Stage 4 found that in countries with higher urbanization rates, the loneliness–suicidal ideation edge weight was stronger (*r*_s = + .639), while protective edge weights from friendship, parental monitoring, and peer support were weaker (*r*_s = − .543 to − .799). All four stages analyzed the same GSHS dataset at different levels of aggregation; the consistency across analyses therefore reflects analytic convergence within a single data source, and independent replication using different adolescent health surveys (e.g., HBSC, YRBSS) is an important next step.

Theoretical Contributions

Hu et al. [12] confirmed the cross-cultural universality of the loneliness–suicide association (pooled OR range: 2.04–3.13). The present study asks a different question: what macro-level conditions are associated with cross-national variation in this association's strength. Abio et al. [11] tested macro-micro interactions in a 33-country LMIC subset without significant results; the present study's wider cross-national range (87 countries, urbanization approximately 15%–100% vs. 15%–65%) and two-stage data-driven approach (SHAP screening followed by GLMM confirmation) may account for the different conclusions. Whether the urbanization–loneliness association attenuates when restricted to LMICs remains an empirical question.

Urbanization rate should be understood as a composite social-environmental variable that may alter the pathological weight of loneliness through co-occurring processes: weakening of traditional kinship networks and increasing population density without proportionate gains in meaningful social connection [27, 28, 43]. A recent meta-analysis of 80 studies (*N* = 539,557) confirmed that urban residence is associated with higher depression prevalence, particularly in developed countries (OR = 1.30) [28], and city-level analyses have identified loneliness and eroded neighborhood cohesion as mediating pathways between urbanization and poor mental health in adults [43]. Whether these mechanisms extend to adolescent suicide risk networks has not been tested. Two complementary theoretical frameworks help specify the mechanism. First, Granovetter's [38] distinction between *strong ties*—dense, emotionally

intimate bonds characteristic of kinship-based communities—and *weak ties*—frequent but shallow contacts typical of urban social environments—offers a structural account. Strong ties function as the primary buffer against distress escalation: they sustain the reciprocal emotional support capable of interrupting the loneliness–suicidal ideation pathway. Rapid urbanization is associated with a shift from strong-tie networks toward weak-tie environments [27], which may reduce this structural buffer and leave distress with fewer sources of relational support. Second, Holt-Lunstad [39] synthesized evidence that social connection functions as an independent determinant of both mental and physical health outcomes, with perceived isolation carrying risk effects comparable in magnitude to established risk factors such as smoking. High-density urban environments generate frequent but shallow contact, which may paradoxically heighten the perceived gap between actual and desired connection—particularly for adolescents, for whom peer belonging is a central developmental task [40]. The Stage 4 findings are consistent with both frameworks: in higher-urbanization countries, the loneliness–suicidal ideation edge strengthened (r_s = + .639) while protective edges from friendship, parental monitoring, and peer support simultaneously weakened (r_s = − .543 to − .799), a pattern consistent with urbanization being associated with weakened social buffering infrastructure rather than simply elevated loneliness prevalence.

Social media penetration is a plausible co-occurring factor [29, 30] (though umbrella reviews of the evidence report mixed and often small effect sizes [31]) that could not be directly measured in the GSHS. After partialing out internet penetration (the closest available proxy), urbanization still predicted loneliness SHAP importance (partial r_s = .452, p = .003), retaining approximately 69% of the original effect. Moreover, 24.3% of the sample was surveyed before 2012, when social media use was minimal in most participating countries, and the GLMM interaction was stable when controlling for survey year (delta-OR < .001). These observations suggest that urbanization captures broader social-environmental restructuring beyond digital connectivity alone [27, 28].

Stage 4 showed that a single variable can occupy systematically different structural positions depending on macro-level context: in higher-urbanization countries, loneliness simultaneously has stronger risk edges and weaker protective edges—information that purely variable-level analysis cannot capture. These cross-national differences should not be equated with urbanization “causing” network structure changes.

A competing hypothesis is that cross-national variation in loneliness SHAP importance reflects greater reporting tendency in higher-urbanization countries (response bias) rather than genuine changes in network position. Two observations argue against this. First, country-level loneliness prevalence was not positively correlated with urbanization (r_s = − .199, p = .073, N = 80), contrary to what reporting bias would predict. Second, Stage 4’s loneliness–SI partial correlation (which controls for other variables and is less sensitive to marginal distributions) was itself positively correlated with urbanization (r_s = + .639). This competing hypothesis is not fully excluded but is inconsistent with the available evidence.

The present findings also complement those of Freije et al. [13] on global trends in adolescent loneliness. Freije et al. documented temporal changes in adolescent loneliness across 38 OECD countries but did not test urbanization rate as an explanatory variable. The present study's cross-sectional analysis, from the perspective of spatial variation (rather than temporal variation), similarly points to an association between urbanization and adolescent loneliness.

Policy Implications

The following implications are conditional on longitudinal confirmation of these cross-sectional patterns and should be treated as hypotheses for future testing rather than established guidelines.

With that caveat, the relationship between urbanization and mental health has received meta-analytic support in adult samples [28] and recent attention in adolescent-focused urban health frameworks [43], but how it relates to adolescent suicide risk network structure remains unexplored. Should future longitudinal work corroborate these patterns, the findings would support tailoring intervention priorities to a country's development stage instead of applying uniform protocols.

In higher-urbanization settings, Stage 4 found that the loneliness–suicidal ideation edge weight is stronger while protective edges from friendship and peer support are weaker. If these patterns are causal, loneliness-focused interventions would be a logical priority—and more specifically, effective programs may need to move beyond generic resilience training toward rebuilding strong-tie opportunities (e.g., sustained cohort-based peer programs rather than one-off social skills workshops).

In lower-urbanization settings, survival-level threats such as hunger and school violence appeared to carry greater weight in suicide risk prediction (Stages 2–3). Pending longitudinal evidence, resource allocation in these contexts may need to prioritize food security and school safety rather than transplanting loneliness intervention programs from high-income countries.

Limitations

First, all GSHS data are cross-sectional, so the four-stage pipeline yields associational evidence only. The GLMM and SHAP analyses used the same data at different levels of aggregation, constituting analytic convergence rather than independent validation [20]. Social media penetration [29, 30] is a plausible unmeasured confounder; after controlling for internet penetration (the closest available proxy), urbanization remained significant (partial r_s = .452, p = .003), but studies with direct social media measurement are needed. Future longitudinal or within-country urban–rural designs [21] would clarify the causal structure.

Second, because the GSHS does not cover the WHO European region, no European countries were included. Replication using HBSC data is a priority.

Third, GSHS variables are single-item self-report measures for which cross-cultural measurement invariance cannot be formally tested [32]. The cultural meaning of "loneliness" may differ across

contexts, and cross-national variation in its network role could partly reflect measurement non-equivalence [33]. The GSHS also samples only in-school adolescents; because school dropout rates are higher in lower-urbanization countries, this could inflate the cross-national gradient.

Fourth, survey years span 2003–2017. This window reflects the most comprehensive publicly available GSHS microdata at the time of analysis; post-2017 data collection has been limited by staggered country participation cycles and COVID-19 school closures [44]. Whether these associations hold in more recent cohorts—particularly given the rapid rise of social media—warrants investigation as newer waves become available.

Fifth, urbanization rate is a composite indicator that cannot be decomposed into sub-mechanisms in the present design, and the interaction effect size was small (OR = 1.096; E-value = 1.37, meaning an unmeasured confounder with moderate associations to both urbanization and the loneliness–SI link could explain the observed interaction). Following Rose's [34] prevention paradox, small shifts in population-level risk distributions may translate into meaningful changes in absolute case numbers across rapidly urbanizing countries, but this argument applies most directly to within-country temporal trends rather than to the between-country cross-sectional comparisons reported here. The clinical relevance awaits evaluation in longitudinal and intervention designs.

Conclusion

Four-stage multi-method analysis of nearly 440,000 adolescents across 87 countries in five WHO regions indicates that although suicidal ideation universally occupies a central position in the risk network (top two in Strength across all regions), the relative role of loneliness in suicide risk prediction is systematically associated with national urbanization levels: in countries with higher urbanization rates, loneliness's risk network connections are stronger while its protective connections are weaker. If these cross-sectional associations are confirmed in longitudinal studies, they would support matching prevention priorities to national development contexts.

Declarations

Funding

The author received no specific funding for this work.

Conflicts of Interest

The author declares no conflicts of interest.

Ethics Approval

This study used publicly available, deidentified secondary data from the WHO GSHS public database. No ethical approval was required for secondary analysis of deidentified public data, consistent with institutional review board guidelines for exempt research.

Consent to Participate

Not applicable. All data were previously collected by WHO-affiliated survey teams with appropriate local ethical approvals and informed consent procedures.

Data Availability

All primary data are publicly available from the WHO GSHS repository (https://www.who.int/teams/noncommunicable-diseases/surveillance/systems-tools/global-school-based-student-health-survey). Country-level macro indicators were obtained from the World Bank Open Data platform and the Hofstede Insights database.

Preregistration

This study was not preregistered. The analytic pipeline was developed iteratively, with the focus on loneliness and urbanization emerging from data-driven screening in Stages 2–3.

Author Contributions

Qingjun Zhu: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Visualization.

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45. Supplemental, Materials
46. STROBE, Checklist

Figures

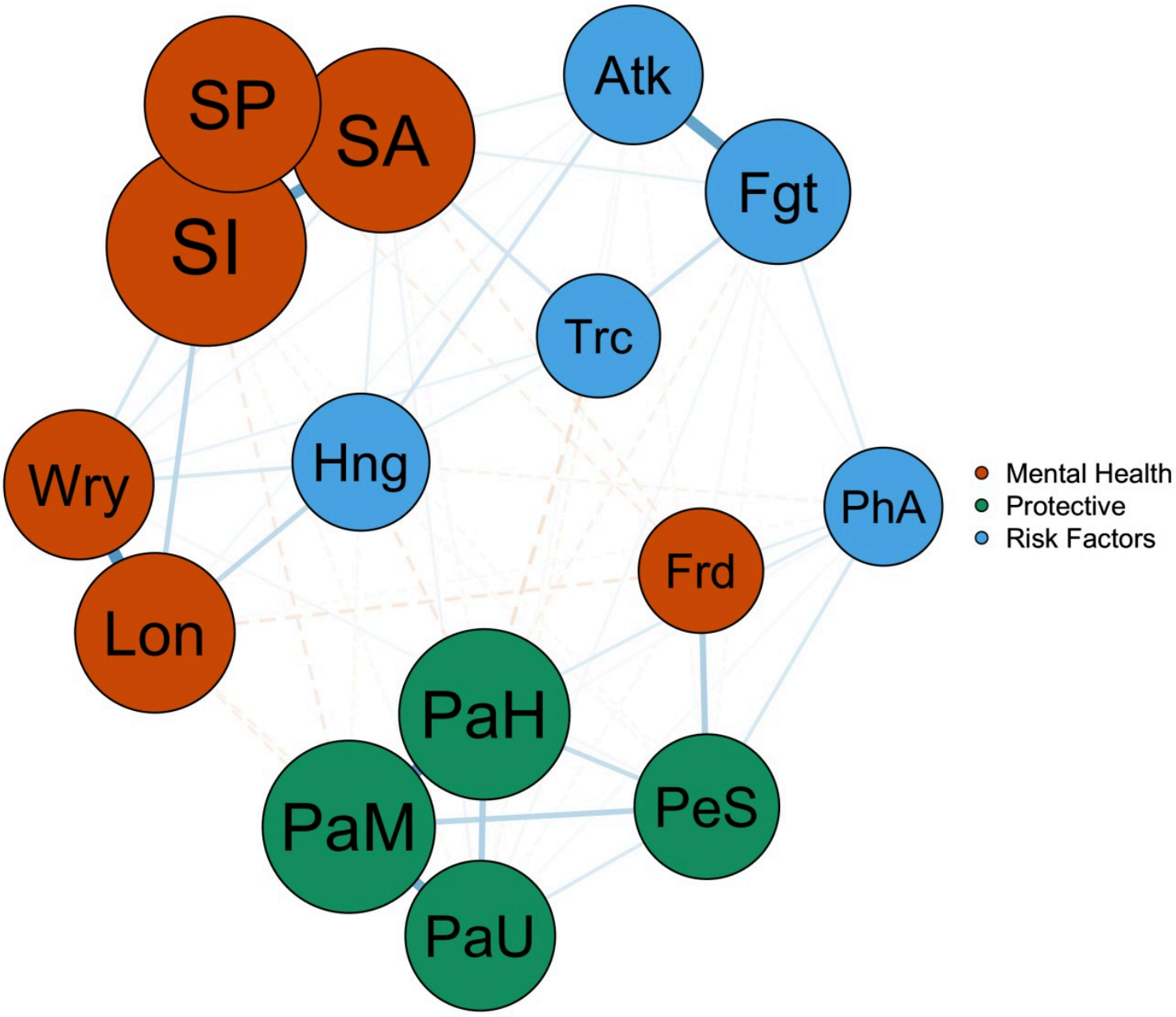


Figure 1

Global adolescent mental health risk network (EBICglasso, *N* = 292,280, 87 countries). Vermillion = mental health, bluish green = protective factors, sky blue = risk factors. Node size proportional to Strength centrality; edge width proportional to partial correlation weight (blue = positive, vermillion dashed = negative). Abbreviations: SI = suicidal ideation, SP = suicide plan, SA = suicide attempt, Lon = loneliness, Wry = worry-insomnia, Frd = close friends, PeS = peer support, PaU = parental understanding, PaM = parental monitoring, PaH = parental homework, Hng = hunger, Atk = physical attack, Fgt = physical fight, PhA = physical activity, Trc = truancy.

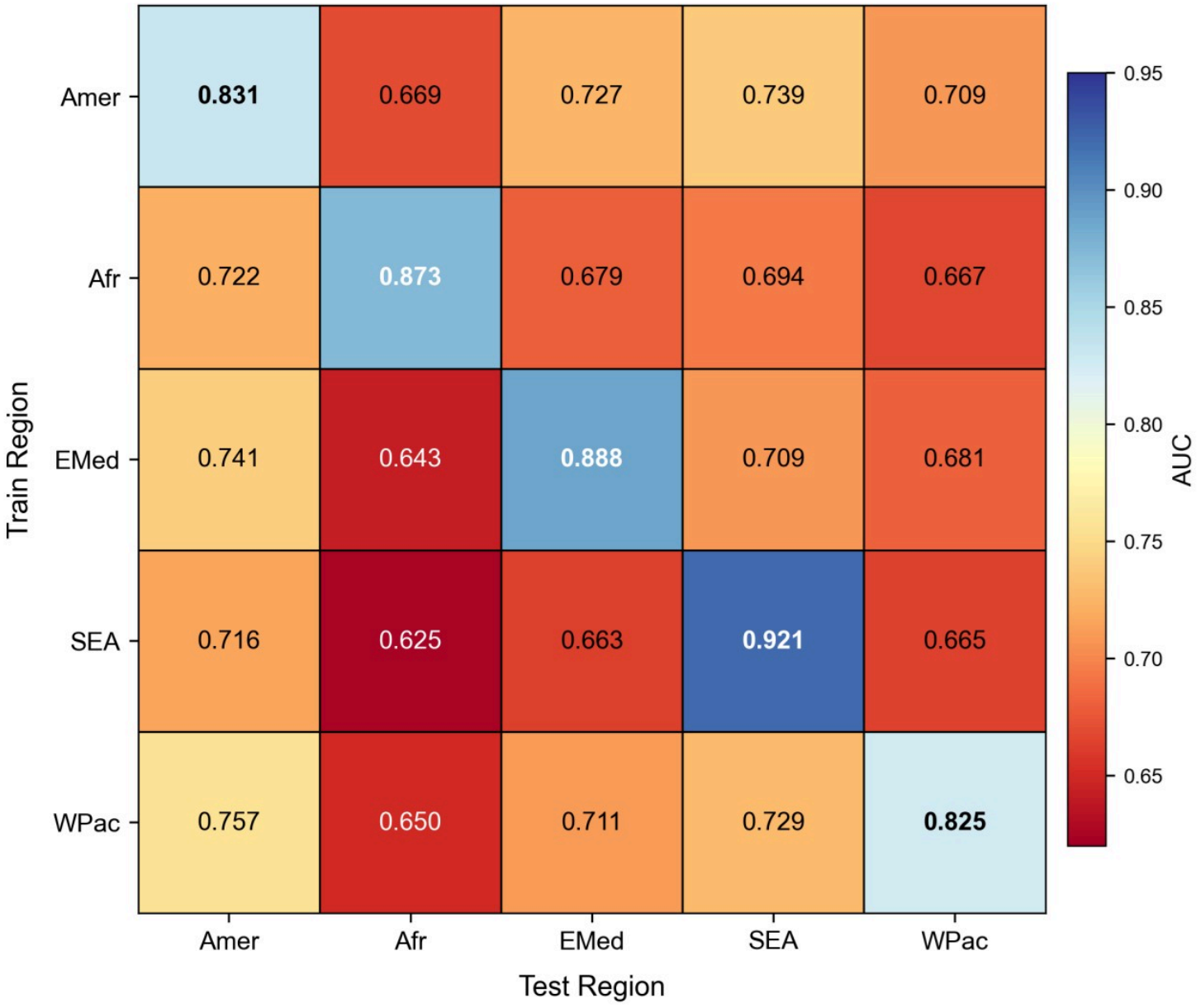


Figure 2

Cross-regional model transfer matrix. Diagonal = within-region AUC (mean = 0.868); off-diagonal = cross-region AUC (mean = 0.695). Mean degradation of 17.3 percentage points. Amer = Americas, Afr = Africa, EMed = Eastern Mediterranean, SEA = South-East Asia, WPac = Western Pacific.

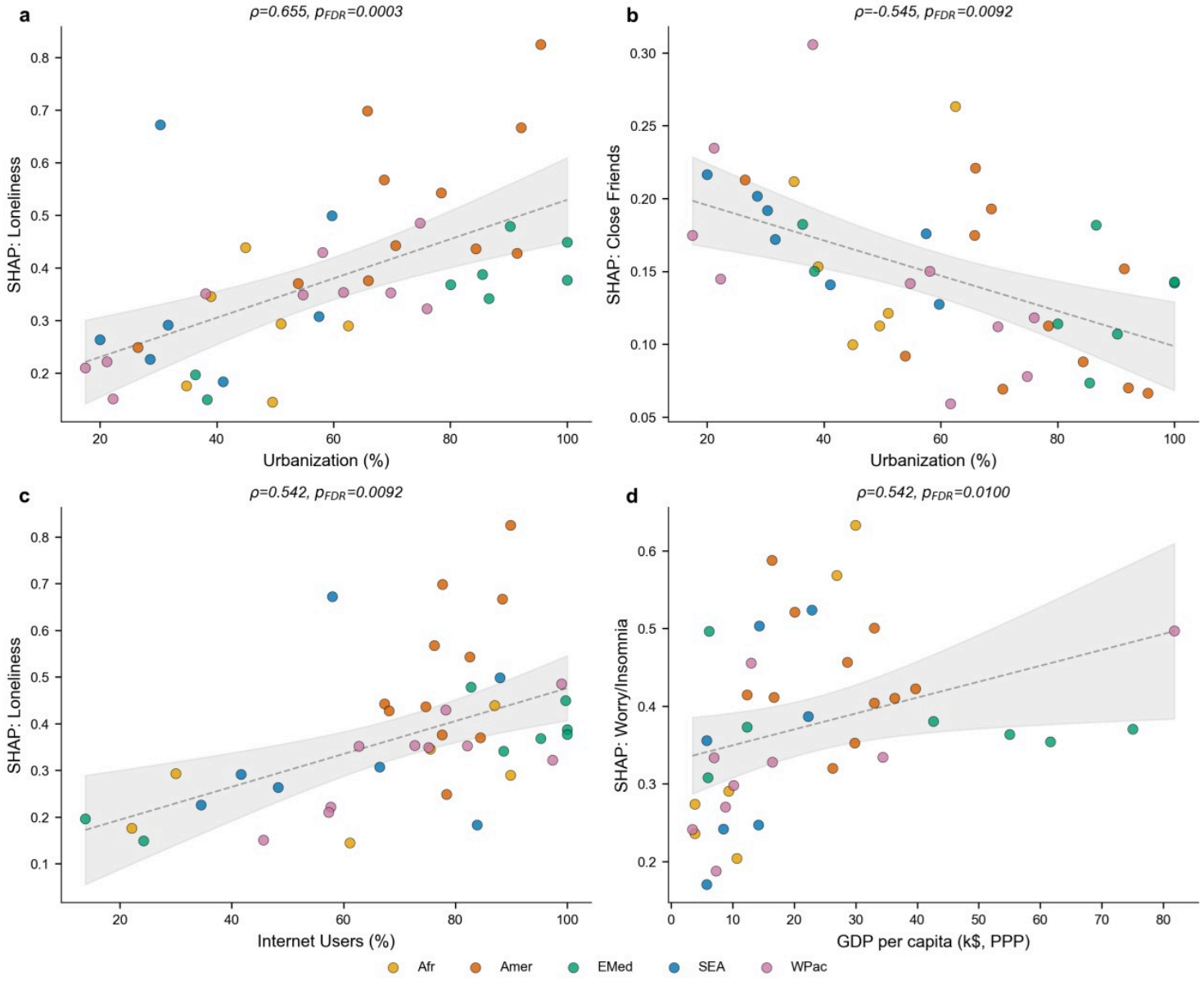


Figure 3

Key macro-micro associations. (a) Urbanization vs. loneliness SHAP (*r*_s = .655, *p*_FDR = .0003). (b) Urbanization vs. close friends SHAP (*r*_s = -.545, *p*_FDR = .009). (c) Internet penetration vs. loneliness SHAP (*r*_s = .542, *p*_FDR = .009). (d) GDP per capita vs. worry-insomnia SHAP (*r*_s = .542, *p*_FDR = .010). Points colored by WHO region.

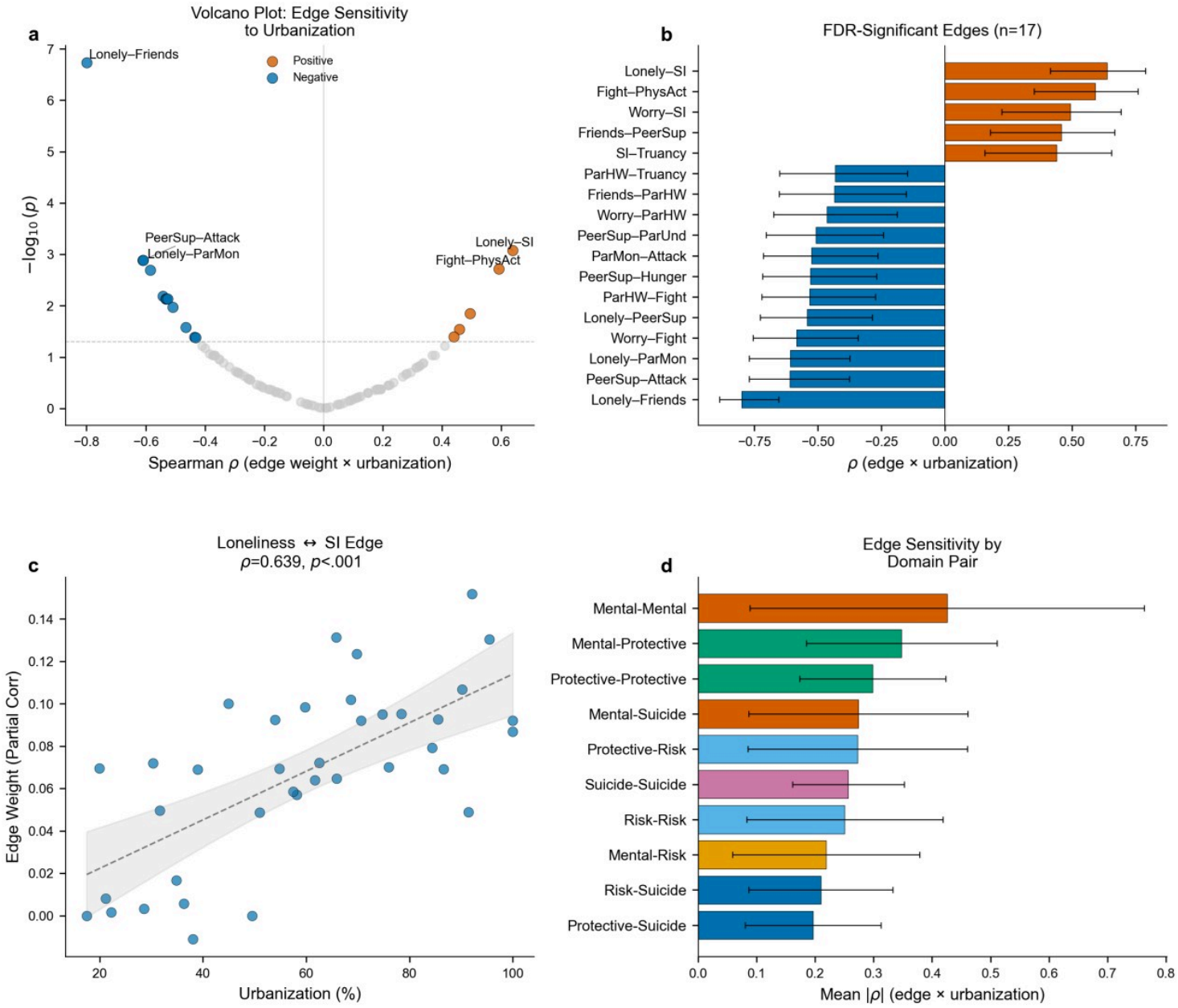


Figure 4

Urbanization and network edge weight associations. (a) Volcano plot of 105 edge–urbanization correlations. (b) FDR-significant edges ranked by *r*_s with 95% CI. (c) Loneliness–SI edge weight vs. urbanization (*r*_s = .639). (d) Mean sensitivity by domain pair (error bars = SD). Blue = negative (protective weakened), vermillion = positive (risk strengthened).

Supplementary Files

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- ESM1.pdf
- ESM2STROBE.docx