Article

Journal of Cross-Cultural Psychology
2021, Vol. 52(8-9) 822–843

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/00220221211040243
journals.sagepub.com/home/jcc
SAGE

A Data-Driven Analysis of Sociocultural, Ecological, and Economic Correlates of Depression Across Nations

Zeyang Li[1], August Wei[2], Vishanth Palanivel[2], and Joshua Conrad Jackson[2]

Abstract

The prevalence of depression varies widely across nations, but we do not yet understand what underlies this variation. Here we use estimates from the Global Burden of Disease study to analyze the correlates of depression across 195 countries and territories. We begin by identifying potential cross-correlates of depression using past clinical and cultural psychology literature. We then take a data-driven approach to modeling which factors correlate with depression in zero-order analyses, and in a multiple regression model that controls for covariation between factors. Our findings reveal several potential correlates of depression, including cultural individualism, daylight hours, divorce rate, and GDP per capita. Cultural individualism is the only factor that remains significant across all our models, even when adjusting for spatial autocorrelation, mental healthcare workers per capita, multicollinearity, and outliers. These findings shed light on how depression varies around the world, the sociocultural and environmental factors that underlie this variation, and potential future directions for the study of culture and mental illness.

Keywords

cultural psychology, clinical/abnormal, environmental/population

Depression is a pervasive mental illness in all world regions (Marcus et al., 2012). Given the prevalence and impact of depression, many studies have investigated its causes and consequences. However, much of this research has investigated biological and structural antecedents of depression within single nations, and we still have limited understanding of why depression may vary from country to country (Johnson et al., 2017; Lumley et al., 2018; Thornicroft & Sartorius, 1993). Austria and the United States are both developed Western nations, but the Global Burden of Disease Network (Liu, He, et al., 2020) estimates that the prevalence of depression is significantly higher in the United States (4.84%) compared to Austria (3.26%). What factors could account for this cross-cultural variation?

[1]Keystone Academy, Beijing, China
[2]University of North Carolina at Chapel Hill, USA

Corresponding Author:
Joshua Conrad Jackson, Kellogg School of Management, Northwestern University, 2211 Campus Drive, Evanston, IL, 60208, USA.
Email: joshua.jackson@kellogg.northwestern.edu

Here we take a data-driven approach to examining cross-cultural variation in depression. We use estimates from the 2017 Global Burden of Disease study, which involved a comprehensive examination of depression across 195 countries and territories, to test which variables might be most strongly linked to depression across nations—defined here as either countries or territories. After reviewing past literature on culture and depression to identify possible correlates to depression, we estimate correlations between a variety of factors and depression prevalence across nations, adjust these estimates based on spatial autocorrelation and outliers, and build a comprehensive regression model. We also consider the role of underreporting, and the potential measurable and unmeasurable characteristics of depression underreporting in cross-cultural analyses. Our ultimate goal is to provide one of the most globally comprehensive multivariate analyses of depression to date, and to test whether different factors that have been implicated in depression by past clinical and cultural psychology literature can predict variation in depression across a large sample of nations.

What Could Explain Global Variation in Depression? A Brief Review of Past Literature

Although there have been few multi-nation studies of depression, there is a large and diverse literature on the potential factors that underlie cultural variation in depression that has focused on case studies, two-culture comparisons, or small cross-cultural samples. These studies have implicated sociocultural, ecological, and economic factors in cross-cultural variation in depression.

Depression and sociocultural factors. Some research on mental health and depression has examined how depression may vary based on dimensions of cultural variation. One prominent dimension is cultural individualism-collectivism, the cultural orientation toward individual identity and autonomy versus collective connectedness and responsibility (Hofstede et al., 2005; Triandis, 1993). There has not been a large literature on depression and individualism, but key studies have suggested that cultural collectivism may be linked with lower rates of depression (Brougham & Haar, 2013). One analysis for example, found that collectivism was linked with a greater sense of familial support during stressful events (Goodwin & Plaza, 2000), and another conceptually related study found that both collectivism and family support negatively predicted suicidal ideation in an Iranian sample (Ariapooran S et al., 2018). Despite these findings, the cross-cultural relationship between individualism-collectivism and depression is still unclear. Some case studies have suggested that there may sometimes be positive associations between depression and collectivism (e.g., Tafarodi & Smith, 2001), and others have argued that individualism-collectivism is more implicated in the events that trigger depression than it is in the prevalence of depression (Chen et al., 2006).

Different studies have tied other dimensions of culture to depression. A cross-cultural analysis of 32 nations found that societies characterized by extreme tightness (very strong norms and harsh punishments for deviance) or extreme looseness (very weak norms and a lack of punishment for deviance) had higher rates of dysthymia, suicide, and physical health ailments compared to countries with moderate tightness-looseness (Harrington et al., 2015). Other studies have found that high-power distance nations have higher than average levels of depression (Arrindell et al., 2003) and summer seasonal affective disorder (Kasof, 2009), which is important to note because power distance correlates highly with both individualism (Hofstede, 1991) and cultural tightness (Gelfand et al., 2011). Reviewing this cross-cultural literature reveals many possible associations between cultural dimensions and depression, but no studies that have tested how multiple cultural dimensions relate to the prevalence of depression in a large and globally representative sample of countries.

Religion, divorce rate, and ethnic heterogeneity represent additional sociocultural factors that could be linked to cross-cultural variation in the prevalence of depression. Many studies now suggest that religiosity can be a protective buffer against mental illness, both because religious belief is associated with hope and optimism (Salsman et al., 2005) and because religion often provides people with church communities that serve as sources of social support (Hovey et al., 2014; Moxey et al., 2011). Like religion, divorce has been linked to risk of depression because it represents a major loss of social support (Chun et al., 2016; Sakyi et al., 2012). Ethnic heterogeneity—the level of ethnic diversity in a nation—could also be related to depression across cultures because immigrants and ethnic minorities are often at a higher risk of mental illnesses, including depression (Alegria, 2016; Zisberg, 2017), and so countries with a higher rate of immigration and more ethnic groups could have higher prevalence rates of depression. Religion, ethnic heterogeneity, and divorce are all intriguing because they often correlate with individualism across geography and history (Grossmann & Varnum, 2015; Talhelm et al., 2014; Vandello & Cohen, 1999; Wood et al., 2016). It is therefore possible that religion, heterogeneity, divorce, and individualism are all linked to depression in a similar way, but that this association is driven primarily by one of the variables.

One final sociocultural factor that we consider is median age. Because of variation in birth rates and life expectancies, nations vary widely in their median age. For example, the median age in Japan is 47.3, more than double the median age in Iraq (20.0) according to the CIA Factbook. Multiple studies have found variation in the prevalence of depression across the lifespan (Brody & Pratt, 2018; Kessler et al., 2010), which makes it plausible that national differences in median age could show a meaningful association with depression prevalence.

Depression and ecological factors. A different body of research has focused on the relationship between depression and ecological factors that occur in people's natural environments. In early studies on the ecology of depression, there was a focus on daylight and weather, with the notion that colder climates with longer winters and less sunlight might be associated with higher rates of depressive symptoms (Molin et al., 1996). More recent studies on seasonal affective disorder have supported the idea that lack of sunlight may increase the risk of depression (Dominiak et al., 2015; Kim, Bang, et al., 2021; Ljubičić et al., 2007). However, longitudinal analyses have not found clear evidence that long-term climate patterns are associated with depression (Huibers et al., 2010), though acute climate disasters may contribute to depressive symptoms associated with post-traumatic stress disorder (Cruz et al., 2020). None of these studies have involved large-scale cross-cultural analyses, but they suggest that cross-cultural variation in the prevalence of depression may be highest in nations with little daylight (especially during winter) and cold temperatures, but also in nations with extreme levels of temperature or precipitation which have an elevated risk of natural disaster. The role of extreme temperature and precipitation has been further explored in cross-cultural research on climate and culture (see Van de Vliert, 2008).

There has also been research on how human-caused damage to the environment relates to depression. For example, depression has now been linked to water and air pollution (Lin et al., 2017; Liu, Chen, et al., 2020; Shao et al., 2021), mold and dampness (Shenassa et al., 2007), malnutrition (Aydoğan et al., 2019; Ghimire et al., 2018; Wei et al., 2018), low-quality housing (Kim, Jeong, et al., 2021), and living in cities (James et al., 2017), although the mechanisms behind some of these associations are still unknown. Nations with high levels of conflict—both with other nations and within the nation—may also have higher rates of depression because of the psychological toll of war and other forms of conflict on mental health (Farhood et al., 2013; Miller & Rasmussen, 2010; Thabet et al., 2004). Taken together, these studies predict that depression may have its highest prevalence in nations with high pollution, poor water quality, a high share of urban residents, high levels of malnutrition and physical illness, and high levels of conflict.

Finally, it is possible that rainfall stability could be associated with depression because of how rainfall shapes culture. According to Welzel's (2013) human emancipation theory, "cool water conditions"—climates characterized by continuous rainfall throughout the year—were important in the rise of cultural individualism and may have contributed to the expansion of human freedom and democracy. For this reason, including Welzel's cool water index is an important control variable in any model of individualism and depression, and a potentially significant correlate of depression across nations.

Depression and economic factors. Economic characteristics may also explain variation in the prevalence of depression across nations. Unstable work, high rates of unemployment, and low earnings have all been linked to higher rates of depression (Haar et al., 2014; Kessler & Bromet, 2013; Levinson et al., 2010). Research also suggests that income inequality may be related to depression. Studies have found associations between income inequality and a range of public health problems ranging from substance abuse to hypertension (Fiscella & Franks, 2000). Income inequality also creates unfavorable social comparisons and more risk-taking (Payne et al., 2017). Perhaps for these reasons, American states with higher levels of income inequality also have a higher prevalence of depression (Pabayo et al., 2014), although it is not clear whether these associations generalize to the national level. Economic factors also comprise technological developments. The growth of internet usage has been especially implicated in depression (Park et al., 2013), especially in adolescents (Park et al., 2016), partly because it might encourage unhealthy social comparisons (Chow & Wan, 2017). This literature suggests that nations with high levels of unemployment, low wealth, high inequality, and perhaps even high levels of internet coverage all may have an elevated prevalence of depression.

Culture and the Underreporting of Depression

Any cross-cultural analysis of depression must also consider the role of underreporting, as systematic patterns of underreporting could lead to false inferences about variation in the prevalence of depression across cultures (Hunt et al., 2003). Underreporting is a particularly pernicious issue in research on culture and mental illness because it could take multiple forms. One form of underreporting involves a simple lack of infrastructure for properly diagnosing and measuring depression. For example, people living in a country without many mental health workers may never be diagnosed with depression, even if they display symptoms. Previous public health research on medical illnesses has addressed this source of underreporting by adjusting estimates based on the number of hospital beds or the number of doctors per capita in a country as proxies for medical infrastructure (e.g., Gelfand et al., 2021; Nsubuga et al., 2018), but a more accurate proxy for global research on mental illness might control for the per capita rate of mental healthcare workers such as psychiatrists and social workers.

However, two forms of underreporting may be difficult to capture through variation in mental health infrastructure. First, mental illness is stigmatized in many cultures, which may lead people to avoid diagnosis or treatment for their symptoms (Botha et al., 2017; Cagliero, 2020; Krendl & Pescosolido, 2020; Zisberg, 2017). To some extent, a cultural stigmatization of mental health is related to the prevalence of mental healthcare workers, since countries with frequent stigmatization of mental health disorders should have less mental healthcare infrastructure. However, controlling for mental health workers per capita may not fully capture cross-cultural variation in the stigma surrounding depression.

Second, depression may also manifest differently across cultures (Dowrick, 2013). Many reviews have raised the possibility of different depression symptoms across nations (Kirmayer et al., 2017), and challenged the notion of a "one-size-fits-all" DSM diagnostic criteria for depression (Manson, 1995), since physicians may fail to diagnose depressive patients who do not express symptoms in culturally normative ways (Lehti et al., 2009). More specific studies have argued that depression is often expressed more somatically in East-Asian countries and other non-Western countries, manifesting through dizziness, nausea, and headaches rather than anhedonia and depressive thoughts (Kalibatseva & Leong, 2018; Kleinman, 2004; Parker et al., 2001). Another study raised the possibility of a culturally emic "materialistic depression" among African immigrants in the United States, focused on wealth disparities and lack of prestige (Azibo, 2013). Culturally emic forms of depression may go unnoticed if doctors use Western-centric diagnostic criteria.

There is still debate about the true range of symptom variation across nations, since self-report measures of depression such as the Hopkins Depression Inventory and the DASS-18 appear to perform well across cultures (Haroz et al., 2016; Oei et al., 2013; Xie et al., 2015), and the personality correlates of depression replicate in both Western and non-Western samples (Boudouda & Gana, 2020). At this point, more research is needed on the best way to quantify and adjust for symptomatology variation across a wide range of nations but controlling for mental healthcare workers per capita may be a method of partially alleviating concerns about underreporting.

Current Research

Here we synthesize literature on culture and depression to conduct a global analysis that examines the correlates of depression across nations and evaluates the robustness of these correlates while attempting to control for underreporting. We draw from past literature to identify potential correlates of depression prevalence and measures that correspond to these correlates and are widely available across nations. We do not intend to test any single theory of depression here. Rather, we hope to understand which sociocultural, environmental, and economic factors can explain variation across a wide range of nations, and whether it is possible to build a highly predictive statistical model of global variation in depression.

We draw our data from a variety of archival sources and across a wide range of nations, prioritizing data that is available across many nations and which relates to past literature on depression and well-being. To assess depression, we use data from the comprehensive Global Burden of Disease study, which used a combination of extensive literature review and Bayesian meta-regression to estimate depression prevalence across 195 countries and territories. Since these data are estimates, we stress that they are not as precise as a large international survey effort to assess depression prevalence around the world using standardized procedures and measures. However, the Global Burden of Disease network uses a variety of weighting and imputation procedures to correct for measurement bias and sparse data. Their data are therefore arguably the highest quality and the most comprehensive currently available source of information on depression around the world.

We also control for underreporting, drawing from a norm in medical research that illnesses will be less often diagnosed—and may be more often stigmatized—in nations that have fewer healthcare workers per capita (Gelfand et al., 2021; Nsubuga et al., 2018). We focus particularly on mental healthcare workers in this analysis. However, this control may not account for variation in depression symptomatology across nations, a point that we return to in our discussion. We have deposited all code and data at https://osf.io/ngrj8/?view_only=b0f07716e6034ec9b9dc83d0111b3a3b so that others can examine, reproduce, and extend our analysis.

Method

Sample

Our full sample consisted of the 195 countries and territories which were available from the Global Burden of Disease (GBD) study. However, some analyses included fewer countries because not all data were available for the full sample. A power analysis suggested that a sample of 195 had 87% power to detect ($p < .05$) a small effect size of $f^2 = .05$, and 94% power of detecting a medium effect size of .15. One strength of this sample is that it is truly global, with countries from every continent, and many smaller countries and territories that are often left out of cross-cultural research.

We assigned a "region" classification to each country using the 37 D-Place regional classifications, which were developed to capture areas of shared ancestry and frequent cultural contact throughout history (Kirby et al., 2016). Examples of D-Place regions include "Northwest Pacific Islands" and "Eastern Europe." Nesting our nations within world regions was a means of controlling for "Galton's problem": the interdependence of datapoints in a cross-cultural analysis. Regressions assume that datapoints are independent, but countries like Italy and Spain have more proximate shared ancestry and cultural contact than countries like Italy and China (Jackson et al., 2021). This interdependence can sometimes result in spurious associations or even Type I or Type II error.

Materials and Measures

Prevalence of depression. We retrieved data on depression prevalence for each of the 195 countries and territories using the GBD study. The GBD studies are international collaborations—consisting of more than 100 collaborators from around the world and organized by the Harvard School of Public Health and the World Health Organization—which provide comprehensive estimates of multiple diseases around the world (see Murray & Lopez, 1997). The goal of these analyses is to quantify multiple factors associated with mental and physical illnesses, including the number of disability-adjusted life years that people lose to illnesses, the average number of years that people live with an illness, and the estimated prevalence of people in each country who are living with the illness. We focused on the prevalence estimates of people living with MDD across countries using the 2017 data, which were the most recent data available (Liu, He, et al., 2020). The process that the GBD studies use to estimate prevalence is described in depth within Stevens et al. (2016) and many other sources, but we also provide a brief overview below.

Estimates of depression prevalence across nations were calculated by the GBD using a systematic review of the literature for studies that measured the prevalence, incidence, duration, and/or excess mortality of depression in different nations. Prevalence in these studies was defined through point (current/past month) or past year prevalence estimates. Lifetime estimates were excluded as recall bias invalidates them as credible measures of a disease. Data were then pooled using DisMod-MR, a Bayesian meta-regression tool developed specifically for the GBD. DisMod-MR is based on a generalized negative binomial model that (a) uses a mathematical model to enforce internal consistency between estimates from different epidemiological parameters, (b) estimates data for countries with few or no available input data based on random effects for country, regions, and their corresponding super-region groupings, and (c) deals with variability in the data due to measurement bias or alternatively ecological factors through the use of study- and country-level covariates. It is important to note that these are estimates derived through a statistical model, rather than raw prevalence indices collected through national surveys.

In the 2017 prevalence data on depression, values ranged as low as 2.20% (Colombia) to 6.23% (Greenland). We considered adjusting these coefficients based on values from prior years. However, estimates were highly reliable across years ($\alpha = .99$) and so we considered the 2017 data to represent stable estimates of depression prevalence that generalized beyond that particular year. Figure 1 displays worldwide variation in the estimated prevalence of depression.

Correlates. The remaining measures represented potential correlates of depression across nations. In the sections below, we report the data source of these correlates, the year(s) that the

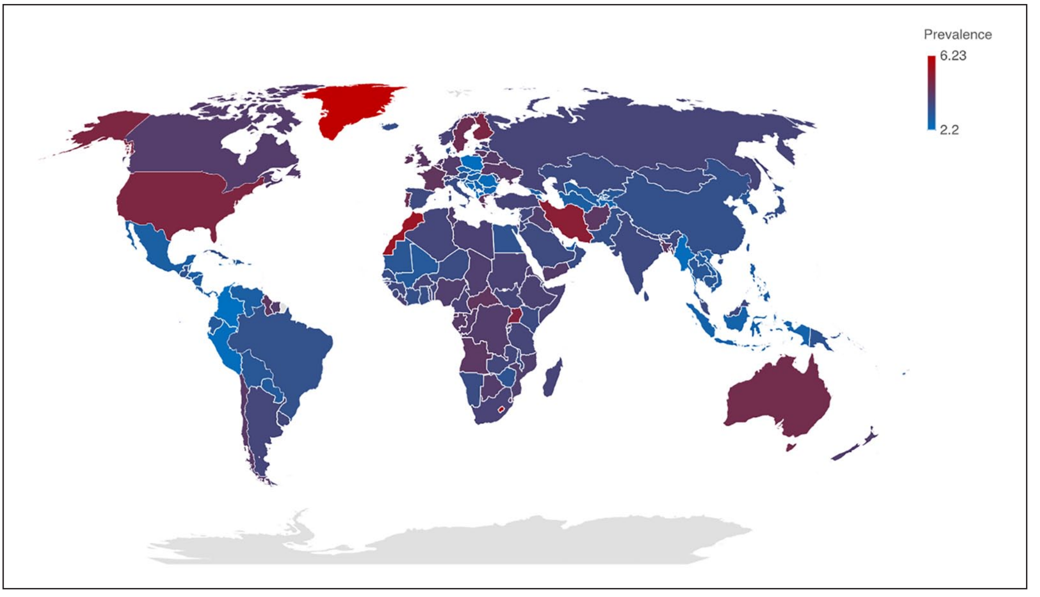

Figure 1. The prevalence of depression across nations, as estimated by the 2017 Global Burden of the Disease study.

data were available, and the number of nations which had available data. Our project page at https://osf.io/ngrj8/?view_only=b0f07716e6034ec9b9dc83d0111b3a3b gives all data on these measures, and also links to the specific webpages where we gained access to the data. We begin by describing our method of quantifying underreporting, and then list correlates in alphabetical order.

Mental healthcare workers per capita. We quantified underreporting using the number of mental healthcare workers per 100,000 employees. We retrieved these data from 147 countries from the World Health Organization (WHO), which surveyed these data between 2013 and 2017. The WHO defined "mental healthcare workers" as psychiatrists, nurses working in the mental healthcare sector, social workers working in the mental healthcare sector, and psychologists working in the mental healthcare sector.

Average income. We operationalized income at the national level through GDP per capita, and used data from the United Nations to estimate GDP per capita for 189 nations. Data were collected in 2019. GDP per capita was measured nominally, meaning that it was in terms of income rather than income, property, and services. The UN standardizes currency differences by putting all figures in terms of United States dollars.

Average temperature. We used data from The Climate Research Unit to retrieve the average yearly temperature in 182 nations in our sample. The data are given in terms of °C and gathered by averaging the maximum and minimum temperature within a day for each country, and then averaging data across 1961 to 1990, which are based on the gridded climatologies contributed by the Climatic Research Unit in 2011.

Pollution. We used data from the organization IQAir to retrieve pollution (in terms of μg/m³) for 94 nations. Higher values indicate greater levels of pollution. All data were from 2017.

Conflict. We downloaded data on conflict from the Uppsala Conflict Data Program across 124 nations. This data divides conflict into "state-based conflict" (conflict between two governments or between a government and a territory or armed organization) and "non-state conflict" (conflict between two organized armed forces where neither is a government). The data represents aggregated deaths in violent conflicts in both categories from 1989 to 2019. We combined the within-nation and between-nation indices of conflict to create a single conflict index for each nation.

Length of shortest day. We used timeanddate.com to retrieve the sunrise and sunset times for each of the 195 nations in our sample. Next, we measured the length of the shortest day by subtracting the sunset time from the sunrise time. Using this metric, we could quantify nations based on the length of their shortest day during winter, when people are most likely to develop depressive symptoms via Seasonal Affective Disorder (SAD; Rosen et al., 1990).

Sunshine duration. In addition to the length of shortest day, we also collected data on variation in each country's rate of total sunshine duration across all seasons. We collected these data from a Wikipedia page which compiled the number of annual sunshine hours for cities around the world for which data were available. We aggregated these data to the nation level by averaging together all the cities reported for each country. This approach meant that we did not assume any single city (e.g., Beijing) was representative of sunshine in a nation (e.g., China).

Divorce rate. We used census data published by governmental statistics offices and displayed on Wikipedia to retrieve data on divorce demography for 97 nations. The data source year varied from 2001 to 2019. These data gave the crude divorce rate (number of divorces divided by the total population $\times$ 1,000), the crude marriage rate, and the ratio of crude divorce rate to crude marriage rate. Here we focus on the crude divorce rate since the crude marriage rate and ratio of divorces to marriages did not show predictive validity above and beyond divorce rate in our models.

Ethnic heterogeneity. We used the Fearon list to capture ethnic diversity. The Fearon list was published in 2003 (Fearon, 2003), and it quantifies ethnic fractionalization using a measure of similarity between languages in a nation in which a value of 1 represents a population that speaks two or more unrelated languages and a value of 0 represents a population where everyone speaks the same language. In past research, the Fearon list has been widely used to explain cross-cultural differences in health policy (Lieberman, 2007) and conflict (Escribà-Folch, 2013).

Income inequality. We used World Bank estimates to retrieve data on income inequality across 161 nations in our sample. Inequality was indexed using the Gini coefficient. A Gini coefficient of 0 would represent a country where everyone receives the same amount of money, whereas a coefficient of 1 would represent a country where a single person has all money.

Individualism-collectivism. We used data from the www.hofstede-insights.com to retrieve collectivism data from 113 nations. These values are the best current estimates from Hofstede's (1991) famous work on characterizing culture. Higher values in this variable indicate greater individualism. However, Hofstede's measure is now several decades old which makes it potentially outdated (Beugelsdijk & Welzel, 2018; Minkov & Kaasa, 2021; Minkov et al., 2017). For this reason, we also collected an alternative index of individualism-collectivism which was published more recently (Minkov et al., 2017), and covered 55 nations in our sample, to replicate our key analyses.

Internet coverage. We used data from the organization "International Telecommunication Union (ITU)" to retrieve the data on the proportion of internet users across 192 nations in our sample. The estimates were derived from household surveys and website subscription data. The estimates were collected across various years in each country, but we always took the nearest available estimate to 2017.

Malnutrition. We retrieved data on malnutrition using information from the United Nations Food and Agriculture Association. Undernourishment was defined in this index as the share of the population with a food energy intake which is lower than that person's requirements, accounting for age, gender, weight, height, and activity levels. The index was available in 2017 for 145 nations.

Median age. We collected data on median age from the UN Population Division, which was available for each of our 195 nations in 2017.

Pathogen prevalence. We measured pathogen prevalence using data published by Murray and Schaller (2010) on the prevalence of nine infectious diseases (leishmania, schistosomes, trypanosomes, leprosy, malaria, typhus, filaria, dengue, and tuberculosis) across geopolitical regions. In particular, these data contained 153 of the nations in our sample. These data are not localized to a particular year. Murray and Schaller calculated these estimates using a variety of data sources, including the National Geographic Society's *Atlas of the World.*

Precipitation. We used data from the Food and Agriculture Organization via the World Bank to calculate precipitation. Precipitation in this context is defined as any kind of water, whether in state of liquid or solid, that falls from the clouds. The index provided data on 180 nations from the 1962 until 2017. We averaged these data across years to obtain a stable precipitation estimate for each country in our sample.

Share of urban population. We obtained data from the United Nations Population Division on the percentage of the population that lived in cities across 190 nations in our sample. These data were developed in the 2018 revision of the "World Urbanization Prospects" report. In this report, there was no single definition of "urban." Instead, the UN used each country's delineations of urban areas to calculate their index. We accessed the data using the World Bank's website.

Religiosity. We quantified religiosity using a 2009 worldwide Gallup poll which asked the question "is religion important in your daily life?" and measured the percentages of people who said "yes" around the world. This figure ranged from 14% in Estonia to 100% in several countries, including Somalia and Oman. The data were available from 146 nations in our sample.

Unemployment rate. We used data from the International Labor Organization (ILO)—which we retrieved through the World Bank—to index unemployment for 192 nations. These data are given in terms of the percentage of people who are not currently working but are willing and able to work for pay, currently available for work, and have actively looked for work. We averaged the index between 2008 and 2020 to obtain stable estimates of unemployment.

Water quality. We retrieved data on water quality from a worldwide analysis by Srebotnjak et al. (2012), which calculated and validated an index of water quality for nations around the world using information about dissolved oxygen, electrical conductivity, pH value, and total nitrogen and phosphorus concentrations. Data were available for 150 nations in our sample.

Cool water index. In his book *Freedom Rising*, Welzel defined "Cool-Water Conditions" as the combination of (1) moderately cold climates, (2) continuous rainfall over all seasons, and (3) permanently navigable waterways. He also developed a cool water index that we incorporated into our analysis.

Analytic Strategy

The goal of our analysis was to identify factors associated with the distribution of depression across nations, and to calculate how these associations changed after adjusting for potential confounds such as underreporting, spatial autocorrelation, and covariation with other factors. We conducted a two-stage approach to this analysis.

Our first stage estimated zero-order associations between each of our correlates and depression. We began by computing linear correlations between depression and each of our other measures, and computing linear and quadratic associations between depression and three factors (cultural tightness, precipitation, and temperature) that could theoretically have significant curvilinear associations with depression across nations. For these three variables, we used regression with standardized variables to simultaneously estimate the linear and quadratic effects.

We also recomputed these simple associations in multilevel regressions where we nested countries within D-Place world regions to control for spatial autocorrelation problem. These models also removed any bivariate outliers that could be exerting any undue influence on the association with depression. We performed this outlier removal by calculating studentized residuals, and then conducting a Bonferroni Outlier Test which uses a *t* distribution to test if the model's largest outlier is significantly different from the other datapoints in each bivariate model. This combination of correlation and multi-level regression allowed us to estimate correlates of cross-cultural variation in depression, and to ensure these correlates were not driven by problematic outliers or interdependent datapoints.

We next conducted a multiple regression to test how correlates of depression performed when they were modeled together. There are two benefits of this multiple regression approach. First, it allowed us to test whether any factors (e.g., average temperature) were correlated with depression simply because of their covariance with a third variable (e.g., sunshine). Second, multiple regression allowed us to build a weighted model which could "predict" values of depression for each nation more accurately than any single variable. We took a stepwise approach to fitting this model in order to avoid saturation. We entered variables one by one, in order of their strongest association with depression in our first analysis (after removing outliers and adjusting for spatial autocorrelation). If a variable increased the model's adjusted R^2 value, we retained it in the model, but if the adjusted R^2 decreased or remained constant, we excluded the variable from the model. After completing this process, we calculated variance inflation factor analysis on the final model to examine potential multicollinearity, adjusted the estimates in a multilevel framework that nested nations within world regions, and explored potential heteroscedasticity of residuals using a Breusch-Pagan test. We focus on the final models in our main text. We also present each individual model within this stepwise process in our Supplemental Materials.

Results

Zero-Order Associations

Depression was significantly associated with several of the variables in our analysis. The strongest positive linear associations were with individualism (both measures), divorce rate, mental healthcare workers, and GDP per capita. In other words, wealthy individualistic countries with high divorce rates and a large share of mental health workers per capita had prevalent depression. We also found negative linear associations with power distance, the length of shortest day, and precipitation, suggesting that countries with low levels of daylight sunshine during winter, drier

Table 1. Zero-Order Correlates of Depression Across Nations.

Variable	Raw association	Adjusted association	$N_{countries}$
Power distance	$r = -.34$, $p < .001$	$\beta = -.23$, $p = .02$	112
Precipitation (linear)	$\beta = -.25$, $p = .002$	$\beta = -.09$, $p = .35$	182
Length of shortest day	$r = -.25$, $p < .001$	$\beta = -.43$, $p < .001$	195
Tightness (quadratic)	$\beta = -.18$, $p = .24$	$\beta = -.08$, $p = .53$	57
Median age	$r = -.13$, $p = .09$	$\beta = -.05$, $p = .56$	186
Average temperature (linear)	$\beta = -.13$, $p = .16$	$\beta = -.14$, $p = .15$	182
Internet coverage	$r = -.08$, $p = .30$	$\beta = -.04$, $p = .63$	192
Pollution	$r = -.07$, $p = .51$	$\beta = -.005$, $p = .22$	94
Water quality	$r = -.07$, $p = .41$	$\beta = .03$, $p = .69$	149
Religiosity	$r = -.05$, $p = .56$	$\beta = -.21$, $p = .03$	145
Precipitation (quadratic)	$\beta = -.04$, $p = .58$	$\beta = -.06$, $p = .44$	182
Average temperature (quadratic)	$\beta = -.04$, $p = .69$	$\beta = .02$, $p = .80$	182
Cool water index	$r = -.006$, $p = .94$	$\beta = .13$, $p = .16$	164
Unemployment rate	$r = .005$, $p = .95$	$\beta = .005$, $p = .94$	192
Income inequality	$r = .04$, $p = .60$	$\beta = .02$, $p = .87$	161
Malnutrition	$r = .05$, $p = .54$	$\beta = .04$, $p = .64$	147
Pathogen prevalence	$r = .07$, $p = .37$	$\beta = .001$, $p = .99$	191
Share of urban population	$r = .08$, $p = .27$	$\beta = .03$, $p = .71$	152
Conflict	$r = .09$, $p = .33$	$\beta = .04$, $p = .57$	124
Sunshine duration	$r = .10$, $p = .27$	$\beta = -.08$, $p = .41$	134
Ethnic heterogeneity	$r = .14$, $p = .05$	$\beta = .11$, $p = .13$	187
GDP per capita	$r = .16$, $p = .03$	$\beta = .05$, $p = .55$	189
Tightness (linear)	$\beta = .18$, $p = 23$	$\beta = .09$, $p = .56$	57
Mental healthcare workers	$r = .22$, $p = .008$	$\beta = .13$, $p = .10$	146
Divorce rate	$r = .32$, $p = .001$	$\beta = .25$, $p = .004$	98
Alternative individualism	$r = .43$, $p = .001$	$\beta = .34$, $p = .04$	55
Individualism	$r = .42$, $p < .001$	$\beta = .37$, $p < .001$	113

Note. Variables here have been ordered by the size of their raw correlation with depression. Some raw associations are reported as standardized betas because they represent standardized coefficients from regression models including both linear and quadratic terms. Adjusted associations control for spatial autocorrelation and significant outliers.

climates, and low levels of power distance had higher rates of depression. No other variables reached significance (see Table 1 and Figure 2).

Recomputing these associations after adjusting for spatial autocorrelation and outliers revealed a slightly different pattern of results. Individualism, divorce rate, power distance, and daylight hours retained their significant associations with depression. However, precipitation, mental healthcare workers per capita, and GDP per capita were no longer associated with depression prevalence. The association between religiosity and depression was also significant and negative while adjusting for spatial autocorrelation, suggesting that more secular countries had higher rates of depression. The effect sizes from these associations are displayed in Figure 2, whereas Table 1 lists the effect size metrics and significance values from both the raw and adjusted models.

Regression Model

Which factors best explained variation across nations when accounting for covariance between predictors in a multiple regression? Our best-fitting regression model included 10 fixed effects,

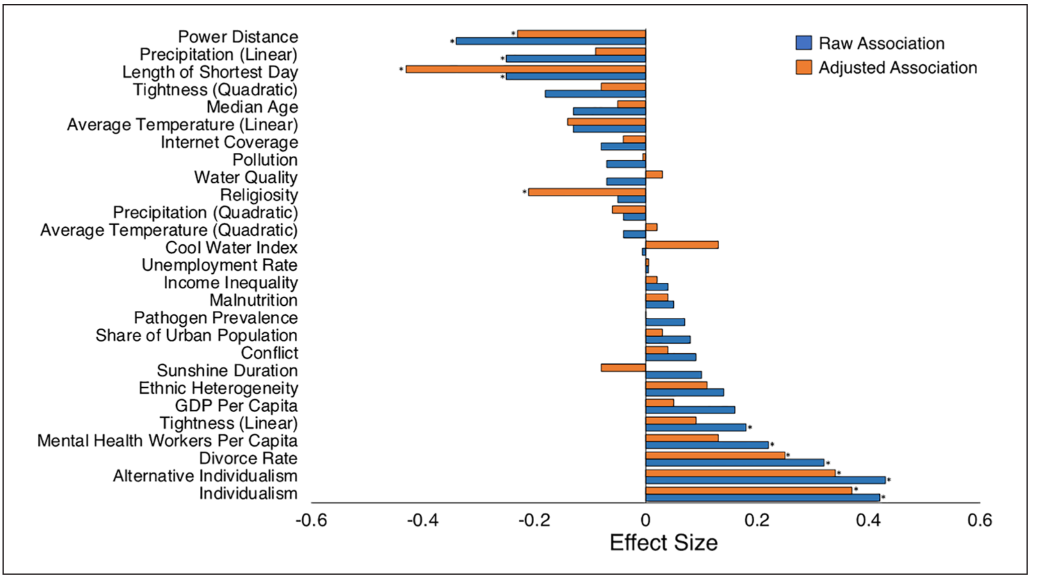

Figure 2. The association between depression prevalence across nations and each of the correlates in a zero-order correlation (blue) and after adjusting for outliers and spatial autocorrelation (orange). Starred associations are statistically significant at $p < .05$.

Table 2. Regression Models of Variation in Depression Across Nations.

	Model 1	Model 2	Model 3	Model 4
Mental health workers per capita	−.001	−.001	−.0001	−.001
Individualism	.04**	.04**	.04**	.04**
Cool water index	−.98	−1.11	.76	−1.21
Sunshine duration	.00003	.00001	.0004	−.0001
Conflict	−.000005	−.000004	.00002	−.000009
Internet coverage	−.007	−.009	−.03	−.009
Water quality	−.008	−.007	.03	−.008
Income inequality	−.01	−.01	−.0008	−.01
Unemployment rate	−.03	−.02	.02	−.02
GDP per capita	−.000008			
Sample size	53	53	28	53
Multiple R^2	.62	.62	.66	.17/.66
Adjusted R^2	.53	.54	.50	NA

Note. Coefficients are unstandardized in these models, which means they are sensitive to differences in units of analysis. There are two multiple R^2 statistics for model 4 because variance can be explained both at the within-region (.17) and between-region (.66) levels. There is no adjusted R^2 coefficient in multilevel models.
*Significance at the <.05 level. **Significance at the <.005 level.

including mental healthcare workers per capita as a proxy for underreporting (see Model 1 in Table 2). In this model, only individualism was significantly associated with depression. The unstandardized coefficient of .04 suggested that, for every one-unit increase in the 1 to 100 individualism scale, there was a .04% increase in the prevalence of depression. In other words, two countries separated by approximately 50 points of individualism (e.g., Brazil and the USA) would be expected to have a 2% difference in the prevalence of depression.

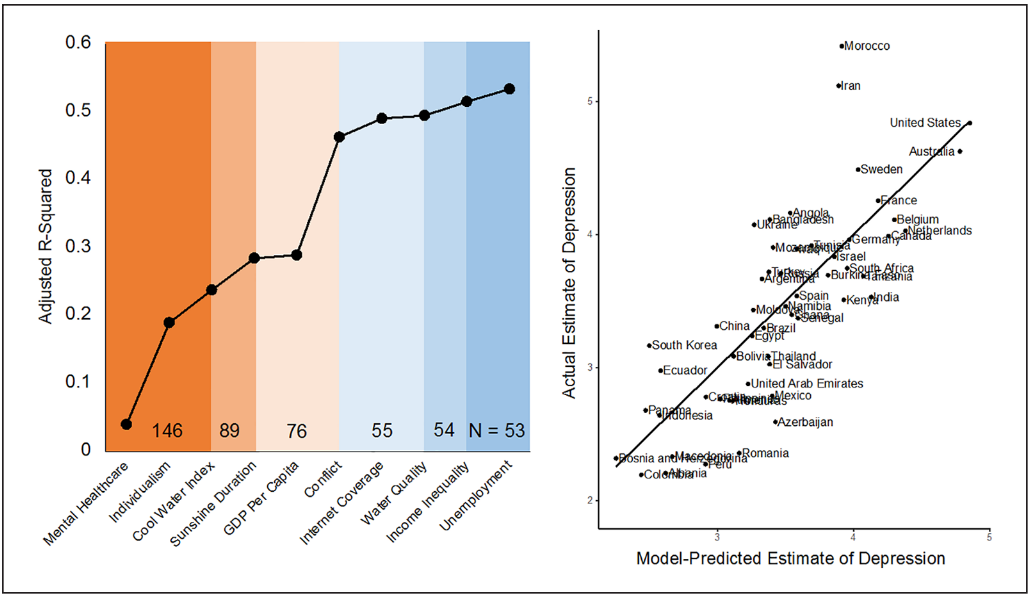

Figure 3. Illustrations of the regression model displayed in Table 2. The left panel illustrates changes in model fit and sample size as each variable was entered into the model in a stepwise fashion. Colors indicate changes in sample size. The right panel illustrates the predicted depression values from the final model regressed against the observed values.

We next examined multicollinearity in this model. In this analysis, only one variable, GDP per capita, had a variance inflation factor of over 5 (5.67), and so we reran our regression model while excluding GDP per capita to examine the robustness of our estimates. In this revised model, the positive effect of individualism remained significant, and no other significant effects emerged (see Model 2 in Table 2). This model showed a higher adjusted R^2 (.54 vs. .53) and showed no evidence of multicollinearity, suggesting that it was an improvement to our original model.

We also performed two additional robustness checks in this multicollinearity-adjusted model. First, we replicated the model with our alternative index of individualism. This replication, displayed as Model 3 in Table 2, showed similar results to our original models. Next, we replicated the model in a multi-level framework with nations nested in D-Place regions. As with Models 1 to 3, this multilevel model found no significant effects other than individualism. We display the results using our primary measure of individualism in Table 2 (Model 4), but the effect of individualism in this multilevel model was similar when we used our alternative measure ($b = .04$, $p = .003$).

How well could our best-fitting and multicollinearity-adjusted model (Table 2, Model 2) predict depression across nations? The model's multiple R^2 value suggested that the model could explain 61.68% of variance in depression across nations, and the adjusted R^2 suggested that it could explain 53.66% of variation after adjusting for multiple predictors. In the left panel of Figure 3, we show the model fit after we added each variable to our stepwise model. The right panel of Figure 3 displays the predicted values of our model regressed against the accurate values. This indicates that, while our model generally performed well, there were some countries (e.g., Iran and Morocco) with higher prevalence rates of depression than our model predicted, which suggests that there may be unmodeled cross-cultural or country-specific factors to be explored in future research.

We note that a model's variance explained can result from multiple factors. For example, a model with fewer datapoints can often show higher R^2 than a model with more datapoints. For this reason, we shade the left panel of Figure 3 to indicate changes in sample size as we added variables into our multiple regression. It is difficult to disentangle changes in R^2 from changes in sample size, but it does appear that fixed effects explained incremental variance in our models, even when the sample size did not change.

Finally, we examined the potential for heteroscedasticity in our multicollinearity-adjusted model. Homoscedasticity, the even distribution of residuals across a regression line, is an assumption of regression, and heteroscedasticity (uneven distribution of residuals) can bias model estimates. Breusch-Pagan tests, which formally test for heteroscedasticity of residuals using a chi-squared distribution, revealed no significant heteroscedasticity in our best-fitting model, $\chi^2=6.13$, $df=9$, $p=.73$, indicating that the model likely met the assumption of homoscedasticity. Our Supplemental Materials include a plot showing the distribution of residuals across the range of predicted depression values to illustrate this homoscedasticity. Our Supplemental Materials also describe outlier analyses for each of our bivariate regressions (Table 1, column 2). A Bonferroni-corrected analysis of studentized residuals in our final multicollinearity-adjusted model revealed no significant outliers (*Bonferroni ps* $>.07$), suggesting that our effects were not driven by any specific countries.

Our Supplemental Materials also provide estimates from each model in our model-building process for both measures of individualism. Across these models, the effect of our primary measure of individualism remains significant, but the effect of our alternative measure is significant in some models and non-significant in others.

Discussion

Why might the prevalence of depression vary across nations? Despite the significant public health consequences of this question, there are surprisingly few multi-nation studies of depression. Here we performed a 195-nation analysis to fill this gap. We aimed to conduct a data-driven investigation of how multiple factors highlighted in past research may relate to cross-cultural variation in depression prevalence. In total, we tested 24 factors that had sufficient data representation and theoretical rationale. We conducted multiple analyses of these variables, ranging from zero-order correlation, to multi-level analysis adjusting for spatial autocorrelation and outliers, to multiple regression models adjusting for covariance between predictors and potential multicollinearity.

Our study revealed several plausible correlates of depression across nations, including environmental factors such as the number of daylight hours during winter and the rate of precipitation, to sociocultural factors such as power distance, cultural individualism-collectivism, and GDP per capita. Some of these factors, such as precipitation, were not robust when controlling for spatial autocorrelation, but most were significant even when excluding potential outliers and adjusting for nestedness within world region. These findings partly explain why countries like Greenland, which have low levels of sunlight during winter, have such high prevalence rates of Major Depressive Disorder.

The most significant contribution of our analysis may be that we show evidence of (and statistically explain) systematic variation in depression across nations, at least as it is measured using DSM-5 diagnostic criteria. We show multiple non-random correlates of depression that suggest that symptoms of depression—at least as they are defined by the DSM—are linked to aspects of people's natural and social environments. Our final model—which included mental healthcare workers per capita, cultural individualism, cool water index, sunshine duration, conflict, internet coverage, water quality, income inequality, and unemployment rate—explained over 60% in variation in depression across nations.

Another advantage of our analysis is that we could test whether zero-order associations involving depression replicated in multiple regressions which controlled for covariation between the different factors. This approach revealed several interesting findings. For example, whereas divorce rate and power distance had significant bivariate associations with depression, they did not reach significance in a multiple regression model controlling for individualism. In fact, individualism was the only association that remained significant across our multiple regression models. The link between depression and individualism also replicated across two different measures, although this link was stronger for our primary measure of individualism than our secondary measure.

We see different reasons why cultural individualism could be associated with depression prevalence. First, it may be that cultural collectivism has protective properties that prevent depression. Some research suggests that people living in collectivist societies may have greater access to family support systems that can buffer against mental illness, in part because there is a greater sense of familial responsibility and a larger proportion of multigenerational households in collectivistic societies (Ariapooran et al., 2018; Goodwin & Plaza, 2000).

An alternative explanation is that depression is systematically under-diagnosed in nations with more collectivistic cultures. Our introduction summarizes research arguing that depression may be expressed more in terms of somatic symptoms like dizziness and nausea in Eastern cultures—which also tend to be more collectivist (Cohen et al., 2016)—compared to Western cultures, and that these different symptoms may lead to systematic underreporting in Eastern nations. The strength of a symptomatology-based argument for the association between individualism and depression is still unclear, however, because depression measures do appear to have measurement equivalence across Eastern and Western nations (Haroz et al., 2016; Oei et al., 2013; Xie et al., 2015). Moreover, the DSM diagnostic criteria have become more open-ended in recent years so that non-traditional symptoms can be diagnosed. If symptomatology does not explain the depression-individualism link, a related possibility is that depression is more stigmatized in collectivist societies. Mental health stigma can prevent people from seeking mental healthcare (Schomerus et al., 2009), and stigma can explain unwillingness to seek help for depression among minority groups within the United States (Campbell & Mowbray, 2016; Interian et al., 2010). If collectivist societies placed more stigma on depression, it could result in widespread underdiagnosis in collectivist nations.

We also identified variables that did not have meaningful zero-order associations but added important contributions to our multiple regression. Adding the cool water index, for example, was associated with a .07 increase in our model's adjusted R^2. This increase resulted because individualism was positively correlated with the cool water index, but the two variables had divergent associations with depression such that nations with more continuous rainfall showed evidence of lower depression prevalence when controlling for individualism (see M7 in Table S1). Controlling for levels of conflict also increased model fit, but this may have been because it resulted in a sample size reduction rather than because it meaningfully predicted variation in depression across nations.

Limitations and Future Directions

This study has several important limitations which we note here. We first emphasize that we are analyzing estimates of depression from the Global Burden of Disease study, rather than prevalence rates that have been gathered using a standardized instrument and survey procedure. These estimates have been rigorously vetted through extensive literature review and Bayesian meta-regression models that account for potential bias and study characteristics, and they have been vetted and analyzed in past research (Stevens et al., 2016). Even though these data are not as reliable as a comprehensive cross-cultural survey using a standardized measurement tool, they may be the best option until an instrument has been developed and validated to show measurement equivalence across nations.

Another important limitation is that we cannot fully disentangle sources of underreporting in our study. We measured underreporting through the prevalence of mental healthcare workers per capita, which is a proxy for a nation's mental health infrastructure and also a rough proxy for a nation's stigmatization of mental illness. However, we did not account for potential variation in depression symptoms across nations, which could further contribute to underreporting. This underreporting issue is part of the more general limitation that our study is correlational. Identifying the correlates of depression is useful for a cross-cultural investigation, but we cannot claim from these data that factors such as cultural individualism cause depression.

A third limitation of our study involves the sources of our data. Although we were able to retrieve data for a variety of fixed effects with theoretical relevance, these data were often not available for all nations and were often not collected in the same year as the depression estimates in this study. Most variables were collected in the 5 years before or after depression was measured, but some factors such as religiosity (2009) and ethnic heterogeneity (2003) were collected several years before our depression estimates. For many factors, this is not a large limitation since characteristics such as ethnic heterogeneity and religiosity tend to be quite stable over time (see Jackson et al., 2021). However, other factors such as internet coverage can vary more rapidly and should be interpreted with caution. For the sake of full transparency, we have uploaded the source data (and years) for each of our fixed effects on our project page at https://osf.io/ngrj8/?view_only=b0f07716e6034ec9b9dc83d0111b3a3b.

Finally, we note that our study focused on main effects rather than interactions. There is now evidence that sociocultural factors can moderate the relationship between depression and many other factors, including perceived self-efficacy (Chen et al., 2006; Smith et al., 2016), physical illnesses such as cancer, diabetes, heart disease (Gholizadeh et al., 2014; Lloyd et al., 2012; Mendenhall, 2016; Renn et al., 2011; Sperry, 2010), and even video game engagement (O'Farrell et al., 2020). We did not examine such interactions in our data because our models already contained many variables, and we felt that including interaction terms would lead to multicollinearity and problematic multiple comparisons. However, we have uploaded all data and code with the hope that more targeted future studies can examine interactions between our fixed effects to explain patterns of cross-cultural variation in depression. Other studies may also seek to add further main effects, such as other dimensions of cultural variance (e.g., Schwartz, 2012) and other potential sources of genetic variance across populations that could be linked to depression (see Minkov & Bond, 2017).

We also encourage three other avenues of future research. First, we invite future research on variation in depression across subgroups within nations. Past research has identified several factors, including gender (Céspedes & Huey, 2008), status as an ethnic minority (Alegria, 2016), status as an immigrant (Zisberg, 2017), or status as a lower caste member (Kohrt et al., 2009), as within-culture correlates of depression. Immigration may be an interesting subgroup to analyze because many studies have shed light on an "immigrant health paradox" where immigrants have lower mortality risk and better mental health than native individuals (John et al., 2012; Markides et al., 2015). Our paper's cross-cultural focus meant that we could not examine these within-cultural factors—which is a limitation of our analysis—but we encourage a study that takes a similar data-driven approach to studying individual differences in depression within nations. Within-country analyses would be particularly useful for explaining variation in depression across large heterogeneous nations such as Russia, China, or the United States.

Second, we also encourage culturally informed interventions that build on our insights to treat depression. It would be insightful to see if interventions targeting familial support and community engagement can alleviate depression in individualistic cultures. Several interventions with social support mechanisms (e.g., peer support, group therapy, spousal involvement in therapy) have claimed to reduce depression symptoms (see Hogan et al., 2002, for a review), but these interventions have typically also included other features (e.g., cognitive behavioral therapy) and no interventions have systematically compared efficacy across individualist and collectivist contexts. If a community or family support intervention eliminated the depression prevalence gap between individualist and collectivist groups, this would provide causal support for familial and community support as a mechanism by which individualism is linked to depression.

Third, we encourage research on how cross-cultural predictors of depression may compare with the cross-cultural predictors of subjective well-being. There has been a large social psychology literature on subjective well-being and culture, which has investigated many of the same factors as clinical psychology literature on depression (see Diener & Suh, 2003). However, the relationship between depression and subjective well-being is still unclear, and some countries (e.g., Denmark, Norway) are famous for having high levels of both depression and well-being (Hendin, 1964). Revealing similarities and differences between the cultural profiles of depression and well-being around the world may hold considerable insights into culture, happiness, and mental health.

Conclusion

Why does depression vary around the world? Here we suggest that depression is integrally tied to factors in people's social, natural, and economic environment. In our analysis, depression prevalence across nations was tied to a variety of environmental and sociocultural factors, including individualism, the length of shortest day, and divorce rate. Our data-driven analysis provides a new chapter in a longstanding effort to understanding depression and its global impact.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Joshua Conrad Jackson https://orcid.org/0000-0002-2947-9815

Supplemental Material

Supplemental material for this article is available online.

References

Alegria, M. (2016). 38.3 effects of social context, culture, and minority status on depression and anxiety. *Journal of the American Academy of Child and Adolescent Psychiatry*, *55*(10), S318–S318.

Ariapooran, S., Heidari, S., Asgari, M., Ashtarian, H., & Khezeli, M. (2018). Individualism-collectivism, social support, resilience and suicidal ideation among women with the experience of the death of a young person. *International Journal of Community Based Nursing and Midwifery*, *6*(3), 250–259.

Arrindell, W. A., Steptoe, A., & Wardle, J. (2003). Higher levels of state depression in masculine than in feminine nations. *Behaviour Research and Therapy*, *41*(7), 809–817.

Aydoğan, S., Ünsal, A., & Arslantaş, D. (2019). Evaluation of malnutrition and depression in elderly people: An epidemiological study in turkey. *European Journal of Public Health*, *29*(44), ckz187.

Azibo, D. A. y. (2013). Unmasking materialistic depression as a mental health problem: Its effect on depression and materialism in an African–United states undergraduate sample. *Journal of Affective Disorders*, *150*(2), 623–628.

Beugelsdijk, S., & Welzel, C. (2018). Dimensions and dynamics of national culture: Synthesizing Hofstede with Inglehart. *Journal of Cross-Cultural Psychology*, *49*(10), 1469–1505.

Botha, F. B., Shamblaw, A. L., & Dozois, D. J. (2017). Reducing the stigma of depression among Asian students: A social norm approach. *Journal of Cross-Cultural Psychology*, *48*(1), 113–131.

Boudouda, N. E., & Gana, K. (2020). Neuroticism, conscientiousness and extraversion interact to predict depression: A confirmation in a non-western culture. *Personality and Individual Differences*, *167*, 110219.

Brody, D. J., & Pratt, L. A. (2018). *Prevalence of depression among adults aged 20 and over: United States, 2013–2016*. National Center for Health Statistics.

Brougham, D., & Haar, J. M. (2013). Collectivism, cultural identity and employee mental health: A study of New Zealand Māori. *Social Indicators Research*, *114*(3), 1143–1160.

Cagliero, D. (2020). Ethical implications of cultural barriers to the depression diagnosis: Conversations with primary care physicians. *Journal of Cross-Cultural Psychology*, *51*(9), 683–701.

Campbell, R. D., & Mowbray, O. (2016). The stigma of depression: Black American experiences. *Journal of Ethnic & Cultural Diversity in Social Work*, *25*(4), 253–269.

Céspedes, Y. M., & Huey, S. J. (2008). Depression in latino adolescents: A cultural discrepancy perspective. *Cultural Diversity & Ethnic Minority Psychology*, *14*(2), 168–172.

Chen, S. X., Chan, W., Bond, M. H., & Stewart, S. M. (2006). The effects of self-efficacy and relationship harmony on depression across cultures: Applying level-oriented and structure-oriented analyses. *Journal of Cross-Cultural Psychology*, *37*(6), 643–658.

Chow, T. S., & Wan, H. Y. (2017). Is there any 'Facebook Depression'? Exploring the moderating roles of neuroticism, facebook social comparison and envy. *Personality and Individual Differences*, *119*, 277–282.

Chun, S., Jang, S., Choi, J., Shin, J., & Park, E. (2016). Long-term effects of parental divorce timing on depression: A population-based longitudinal study. *International Journal of Social Psychiatry*, *62*(7), 645–650.

Cohen, A. B., Wu, M. S., & Miller, J. (2016). Religion and culture: Individualism and collectivism in the East and West. *Journal of Cross-Cultural Psychology*, *47*(9), 1236–1249.

Cruz, J., White, P. C. L., Bell, A., & Coventry, P. A. (2020). Effect of extreme weather events on mental health: A narrative synthesis and meta-analysis for the UK. *International Journal of Environmental Research and Public Health*, *17*(22), 1–17.

Diener, E., & Suh, E. M. (Eds.). (2003). *Culture and subjective well-being*. MIT Press.

Dominiak, M., Swiecicki, L., & Rybakowski, J. (2015). Psychiatric hospitalizations for affective disorders in warsaw, poland: Effect of season and intensity of sunlight. *Psychiatry Research*, *229*(1–2), 287–294.

Dowrick, C. (2013). Depression as a culture-bound syndrome: Implications for primary care. *British Journal of General Practice*, *63*(610), 229–230.

Escribà-Folch, A. (2013). Repression, political threats, and survival under autocracy. *International Political Science Review*, *34*(5), 543–560.

Farhood, L., Dimassi, H., & Strauss, N. L. (2013). Understanding post-conflict mental health: Assessment of PTSD, depression, general health and life events in civilian population one year after the 2006 war in south Lebanon. *Journal of Traumatic Stress Disorders & Treatment*, *2*(2), 1–8.

Fearon, J. D. (2003). Ethnic and cultural diversity by country. *Journal of Economic Growth*, *8*(2), 195–222.

Fiscella, K., & Franks, P. (2000). Individual income, income inequality, health, and mortality: What are the relationships? *Health Services Research*, *35*(1 Pt 2), 307–318.

Gelfand, M. J., Jackson, J. C., Pan, X., Nau, D., Pieper, D., Denison, E., & Wang, M. (2021). *The relationship between cultural tightness–looseness and COVID-19 cases and deaths: A global analysis* (Vol. 5, pp. e135–e144). The Lancet Planetary Health.

Gelfand, M. J., Raver, J. L., Nishii, L., Leslie, L. M., Lun, J., Lim, B. C., Duan, L., Almaliach, A., Ang, S., Arnadottir, J., Aycan, Z., Boehnke, K., Boski, P., Cabecinhas, R., Chan, D., Chhokar, J., D'Amato, A., Ferrer, M., Fischlmayr, I. C., . . . Yamaguchi, S. (2011). Differences between tight and loose cultures: A 33-nation study. *Science*, *332*(6033), 1100–1104.

Ghimire, S., Baral, B. K., Pokhrel, B. R., Pokhrel, A., Acharya, A., Amatya, D., Amatya, P., & Mishra, S. R. (2018). Depression, malnutrition, and health-related quality of life among nepali older patients. *BMC Geriatrics*, *18*(1), 191–191.

Gholizadeh, L., Davidson, P. M., Heydari, M., & Salamonson, Y. (2014). Heart disease and depression: Is culture a factor? *Journal of Transcultural Nursing*, *25*(3), 290–295.

Goodwin, R., & Plaza, S. (2000). Perceived and received social support in two cultures: Collectivism and support among British and Spanish students. *Journal of Social and Personal Relationships*, *17*(2), 282–291.

Grossmann, I., & Varnum, M. E. (2015). Social structure, infectious diseases, disasters, secularism, and cultural change in America. *Psychological Science*, *26*(3), 311–324.

Haar, J. M., Russo, M., Suñe, A., & Ollier-Malaterre, A. (2014). Outcomes of work–life balance on job satisfaction, life satisfaction and mental health: A study across seven cultures. *Journal of Vocational Behavior*, *85*(3), 361–373.

Haroz, E. E., Bolton, P., Gross, A., Chan, K. S., Michalopoulos, L., & Bass, J. (2016). Depression symptoms across cultures: An IRT analysis of standard depression symptoms using data from eight countries. *Social Psychiatry and Psychiatric Epidemiology*, *51*(7), 981–991.

Harrington, J. R., Boski, P., & Gelfand, M. J. (2015). Culture and national well-being: Should societies emphasize freedom or constraint? *PLoS One*, *10*(6), e0127173.

Hendin, H. (1964). *Suicide and Scandinavia*. Gruve & Stratton.

Hofstede, G., Hofstede, G. J., & Minkov, M. (2005). *Cultures and organizations: Software of the mind* (Vol. 2). McGraw-Hill.

Hogan, B. E., Linden, W., & Najarian, B. (2002). Social support interventions: Do they work? *Clinical Psychology Review*, *22*(3), 383–442.

Hovey, J. D., Hurtado, G., Morales, L. R., & Seligman, L. D. (2014). Religion-based emotional social support mediates the relationship between intrinsic religiosity and mental health. *Archives of Suicide Research*, *18*(4), 376–391.

Huibers, M. J. H., de Graaf, L. E., Peeters, F. P. M. L., & Arntz, A. (2010). Does the weather make us sad? Meteorological determinants of mood and depression in the general population. *Psychiatry Research*, *180*(2–3), 143–146.

Hunt, M., Auriemma, J., & Cashaw, A. C. (2003). Self-report bias and underreporting of depression on the BDI-II. *Journal of Personality Assessment*, *80*(1), 26–30.

Interian, A., Ang, A., Gara, M. A., Link, B. G., Rodriguez, M. A., & Vega, W. A. (2010). Stigma and depression treatment utilization among Latinos: Utility of four stigma measures. *Psychiatric Services*, *61*(4), 373–379.

Jackson, J., Watts, J., List, J. M., Drabble, R., & Lindquist, K. (2021). *From text to thought: How analyzing language can advance psychological science*. Perspectives on Psychological Science.

James, P., Hart, J. E., Banay, R. F., Laden, F., & Signorello, L. B. (2017). Built environment and depression in low-income African Americans and whites. *American Journal of Preventive Medicine*, *52*(1), 74–84.

John, D. A., de Castro, A. B., Martin, D. P., Duran, B., & Takeuchi, D. T. (2012). Does an immigrant health paradox exist among Asian Americans? Associations of nativity and occupational class with self-rated health and mental disorders. *Social Science & Medicine*, *75*(12), 2085–2098.

Johnson, L. R., Chin, E. G., Kajumba, M., Kizito, S., & Bangirana, P. (2017). Views on depression from traditional healing and psychiatry clinics in Uganda: Perspectives from patients and their providers. *Journal of Cross-Cultural Psychology*, *48*(2), 243–261.

Kalibatseva, Z., & Leong, F. T. L. (2018). Cultural factors, depressive and somatic symptoms among Chinese American and European American college students. *Journal of Cross-Cultural Psychology*, *49*(10), 1556–1572.

Kasof, J. (2009). Cultural variation in seasonal depression: Cross-national differences in winter versus summer patterns of seasonal affective disorder. *Journal of Affective Disorders*, *115*(1–2), 79–86.

Kessler, R. C., Birnbaum, H. G., Shahly, V., Bromet, E., Hwang, I., McLaughlin, K. A., Sampson, N., Andrade, L. H., de Girolamo, G., Demyttenaere, K., Haro, J. M., Karam, A. N., Kostyuchenko, S., Kovess, V., Lara, C., Levinson, D., Matschinger, H., Nakane, Y., Browne, M. O., . . . Stein, D. J. (2010). Age differences in the prevalence and co-morbidity of DSM-IV major depressive episodes: Results from the WHO World Mental Health survey initiative. *Depression and Anxiety*, *27*(4), 351–364.

Kessler, R. C., & Bromet, E. J. (2013). The epidemiology of depression across cultures. *Annual Review of Public Health*, *34*(1), 119–138.

Kim, S., Jeong, W., Jang, B. N., Park, E. C., & Jang, S. I. (2021). Associations between substandard housing and depression: Insights from the Korea welfare panel study. *BMC Psychiatry*, *21*(1), 12–12.

Kim, S. Y., Bang, M., Wee, J. H., Min, C., Yoo, D. M., Han, S. M., Kim, S., & Choi, H. G. (2021). Short- and long-term exposure to air pollution and lack of sunlight are associated with an increased risk of depression: A nested case-control study using meteorological data and national sample cohort data. *The Science of the Total Environment*, *757*, 143960–143960.

Kirby, K. R., Gray, R. D., Greenhill, S. J., Jordan, F. M., Gomes-Ng, S., Bibiko, H. J., Blasi, D. E., Botero, C. A., Bowern, C., Ember, C. R., Leehr, D., Low, B. S., McCarter, J., Divale, W., & Gavin, M. C. (2016). D-PLACE: A global database of cultural, linguistic and environmental diversity. *PLoS One*, *11*(7), e0158391.

Kirmayer, L. J., Gomez-Carrillo, A., & Veissière, S. (2017). Culture and depression in global mental health: An ecosocial approach to the phenomenology of psychiatric disorders. *Social Science & Medicine*, *183*, 163–168.

Kleinman, A. (2004). Culture and depression. *New England Journal of Medicine*, *351*(10), 951–953.

Kohrt, B. A., Speckman, R. A., Kunz, R. D., Baldwin, J. L., Upadhaya, N., Acharya, N. R., Sharma, V. D., Nepal, M. K., & Worthman, C. M. (2009). Culture in psychiatric epidemiology: Using ethnography and multiple mediator models to assess the relationship of caste with depression and anxiety in nepal. *Annals of Human Biology*, *36*(3), 261–280.

Krendl, A. C., & Pescosolido, B. A. (2020). Countries and cultural differences in the stigma of mental illness: The east–west divide. *Journal of Cross-Cultural Psychology*, *51*(2), 149–167.

Lehti, A., Hammarström, A., & Mattsson, B. (2009). Recognition of depression in people of different cultures: A qualitative study. *BMC Family Practice*, *10*(1), 53–53.

Levinson, D., Lakoma, M. D., Petukhova, M., Schoenbaum, M., Zaslavsky, A. M., Angermeyer, M., Borges, G., Bruffaerts, R., de Girolamo, G., de Graaf, R., Gureje, O., Haro, J. M., Hu, C., Karam, A. N., Kawakami, N., Lee, S., Lepine, J. P., Browne, M. O., Okoliyski, M. . . ., & Kessler, R. C. (2010). Associations of serious mental illness with earnings: Results from the WHO World mental health surveys. *The British Journal of Psychiatry*, *197*(2), 114–121.

Lieberman, E. S. (2007). Ethnic politics, risk, and policy-making. *Comparative Political Studies*, *40*(12), 1407–1432.

Lin, H., Guo, Y., Kowal, P., Airhihenbuwa, C. O., Di, Q., Zheng, Y., Zhao, X., Vaughn, M. G., Howard, S., Schootman, M., Salinas-Rodriguez, A., Yawson, A. E., Arokiasamy, P., Manrique-Espinoza, B. S., Biritwum, R. B., Rule, S. P., Minicuci, N., Naidoo, N., Chatterji, S., . . . Wu, F. (2017). Exposure to air pollution and tobacco smoking and their combined effects on depression in six low- and middle-income countries. *The British Journal of Psychiatry*, *211*(3), 157–162.

Liu, Q., He, H., Yang, J., Feng, X., Zhao, F., & Lyu, J. (2020). Changes in the global burden of depression from 1990 to 2017: Findings from the global burden of disease study. *Journal of Psychiatric Research*, *126*, 134–140.

Ljubičić, Đ., Stipčević, T., Pivac, N., Jakovljević, M., & Mück-šeler, D. (2007). The influence of daylight exposure on platelet 5-HT levels in patients with major depression and schizophrenia. *Journal of Photochemistry and Photobiology B Biology*, *89*(2–3), 63–69.

Lloyd, C. E., Roy, T., Nouwen, A., & Chauhan, A. M. (2012). Epidemiology of depression in diabetes: International and cross-cultural issues. *Journal of Affective Disorders*, *142* Suppl, S22–S29.

Lumley, M., Katsikitis, M., & Statham, D. (2018). Depression, anxiety, and acculturative stress among resettled Bhutanese refugees in Australia. *Journal of Cross-Cultural Psychology*, *49*(8), 1269–1282.

Manson, S. M. (1995). Culture and major depression. *Psychiatric Clinics of North America*, *18*(3), 487–501.

Marcus, M., Yasamy, T. Y., Ommeren, M., Chisholm, D., & Saxena, S. (2012). *Depression: A global health concern. In depression: A global crisis* (pp. 6–8). World Federation for Mental Health.

Markides, K. S., Rote, S., Scott, R. A., & Buchmann, M. C. (2015). Immigrant health paradox. In R. A. Scott & M. C. Buchmann (Eds.), *Emerging trends in the social and behavioral sciences: An interdisciplinary, searchable, and linkable resource* (pp. 1–15). John Wiley and Sons.

Mendenhall, E. (2016). Beyond comorbidity: A critical perspective of syndemic depression and diabetes in cross-cultural contexts. *Medical Anthropology Quarterly*, *30*(4), 462–478.

Miller, K. E., & Rasmussen, A. (2010). War exposure, daily stressors, and mental health in conflict and post-conflict settings: Bridging the divide between trauma-focused and psychosocial frameworks. *Social Science & Medicine*, *70*(1), 7–16.

Minkov, M., & Bond, M. H. (2017). A genetic component to national differences in happiness. *Journal of Happiness Studies*, *18*(2), 321–340.
Minkov, M., Dutt, P., Schachner, M., Morales, O., Sanchez, C., Jandosova, J., Khassenbekov, Y., & Mudd, B. (2017). A revision of Hofstede's individualism-collectivism dimension. *Cross Cultural & Strategic Management*, *24*, 386–404.
Minkov, M., & Kaasa, A. (2021). A test of Hofstede's model of culture following his own approach. *Cross Cultural & Strategic Management*, *28*, 384–406. https://doi.org/10.1108/ccsm-05-2020-0120
Molin, J., Mellerup, E., Bolwig, T., Scheike, T., & Dam, H. (1996). The influence of climate on development of winter depression. *Journal of Affective Disorders*, *37*(2–3), 151–155.
Moxey, A., McEvoy, M., Bowe, S., & Attia, J. (2011). Spirituality, religion, social support and health among older Australian adults. *Australasian Journal on Ageing*, *30*(2), 82–88.
Murray, C. J., & Lopez, A. D. (1997). Global mortality, disability, and the contribution of risk factors: Global burden of disease study. *Lancet*, *349*(9063), 1436–1442.
Murray, D. R., & Schaller, M. (2010). Historical prevalence of infectious diseases within 230 geopolitical regions: A tool for investigating origins of culture. *Journal of Cross-Cultural Psychology*, *41*(1), 99–108.
Nsubuga, F., Luzze, H., Ampeire, I., Kasasa, S., Toliva, O. B., & Riolexus, A. A. (2018). Factors that affect immunization data quality in Kabarole district, Uganda. *PLoS One*, *13*(9), e0203747.
O'Farrell, D. L., Baynes, K., Pontes, H. M., Griffiths, M. D., & Stavropoulos, V. (2020). Depression and disordered gaming: Does culture matter? *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-020-00231-1
Oei, T. P., Sawang, S., Goh, Y. W., & Mukhtar, F. (2013). Using the depression anxiety stress scale 21 (DASS-21) across cultures. *International Journal of Psychology*, *48*(6), 1018–1029.
Pabayo, R., Kawachi, I., & Gilman, S. E. (2014). Income inequality among American states and the incidence of major depression. *Journal of Epidemiology and Community Health*, *68*(2), 110–115.
Parker, G., Gladstone, G., & Chee, K. T. (2001). Depression in the planet's largest ethnic group: The chinese. *American Journal of Psychiatry*, *158*(6), 857–864.
Park, J., Lee, D. S., Shablack, H., Verduyn, P., Deldin, P., Ybarra, O., Jonides, J., & Kross, E. (2016). When perceptions defy reality: The relationships between depression and actual and perceived Facebook social support. *Journal of Affective Disorders*, *200*, 37–44.
Park, S., Hong, K. E. M., Park, E. J., Ha, K. S., & Yoo, H. J. (2013). The association between problematic internet use and depression, suicidal ideation and bipolar disorder symptoms in Korean adolescents. *Australian and New Zealand Journal of Psychiatry*, *47*(2), 153–159.
Payne, B. K., Brown-Iannuzzi, J. L., & Hannay, J. W. (2017). Economic inequality increases risk taking. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(18), 4643–4648.
Renn, B. N., Feliciano, L., & Segal, D. L. (2011). The bidirectional relationship of depression and diabetes: A systematic review. *Clinical Psychology Review*, *31*(8), 1239–1246.
Rosen, L. N., Targum, S. D., Terman, M., Bryant, M. J., Hoffman, H., Kasper, S. F., Hamovit, J. R., Docherty, J. P., Welch, B., & Rosenthal, N. E. (1990). Prevalence of seasonal affective disorder at four latitudes. *Psychiatry Research*, *31*(2), 131–144.
Sakyi, K. S., Melchior, M., Chollet, A., & Surkan, P. J. (2012). The combined effects of parental divorce and parental history of depression on cannabis use in young adults in France. *Drug and Alcohol Dependence*, *126*(1–2), 195–199.
Salsman, J. M., Brown, T. L., Brechting, E. H., & Carlson, C. R. (2005). The link between religion and spirituality and psychological adjustment: The mediating role of optimism and social support. *Personality and Social Psychology Bulletin*, *31*(4), 522–535.
Schomerus, G., Matschinger, H., & Angermeyer, M. C. (2009). The stigma of psychiatric treatment and help-seeking intentions for depression. *European Archives of Psychiatry and Clinical Neuroscience*, *259*(5), 298–306.
Schwartz, S. H. (2012). An overview of the Schwartz theory of basic values. *Online Readings in Psychology and Culture*, *2*(1), 2307–0919.
Shao, J., Ge, T., Liu, Y., Zhao, Z., & Xia, Y. (2021). Longitudinal associations between household solid fuel use and depression in middle-aged and older chinese population: A cohort study. *Ecotoxicology and Environmental Safety*, *209*, 111833.

Shenassa, E. D., Daskalakis, C., Liebhaber, A., Braubach, M., & Brown, M. (2007). Dampness and mold in the home and depression: An examination of mold-related illness and perceived control of one's home as possible depression pathways. *American Journal of Public Health*, *97*(10), 1893–1899.

Smith, P. B., Ahmad, A. H., Owe, E., Celikkol, G. C., Ping, H., Gavreliuc, A., Chobthamkit, P., Rizwan, M., Chen, S. X., Teh, H. B., & Vignoles, V. L. (2016). Nation-level moderators of the extent to which self-efficacy and relationship harmony predict students' depression and life satisfaction. *Journal of Cross-Cultural Psychology*, *47*(6), 818–834.

Sperry, L. (2010). Breast cancer, depression, culture, and marital conflict. *Family Journal*, *18*(1), 62–65.

Srebotnjak, T., Carr, G., de Sherbinin, A., & Rickwood, C. (2012). A global water quality index and hot-deck imputation of missing data. *Ecological Indicators*, *17*, 108–119.

Stevens, G. A., Alkema, L., Black, R. E., Boerma, J. T., Collins, G. S., Ezzati, M., Grove, J. T., Hogan, D. R., Hogan, M. C., Horton, R., Lawn, J. E., Marušić, A., Mathers, C. D., Murray, C. J., Rudan, I., Salomon, J. A., Simpson, P. J., Vos, T., & Welch, V., & GATHER Working Group. (2016). Correction: Guidelines for accurate and transparent health estimates reporting: The GATHER statement. *PLoS Medicine*, *13*(8), e1002116.

Tafarodi, R. W., & Smith, A. J. (2001). Individualism–collectivism and depressive sensitivity to life events: The case of Malaysian sojourners. *International Journal of Intercultural Relations*, *25*(1), 73–88.

Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X., & Kitayama, S. (2014). Large-scale psychological differences within China explained by rice versus wheat agriculture. *Science*, *344*(6184), 603–608.

Thabet, A. A., Abed, Y., & Vostanis, P. (2004). Comorbidity of PTSD and depression among refugee children during war conflict. *Journal of Child Psychology and Psychiatry*, *45*(3), 533–542.

Thornicroft, G., & Sartorius, N. (1993). The course and outcome of depression in different cultures: 10-year follow-up of the WHO collaborative study on the assessment of depressive disorders. *Psychological Medicine*, *23*(4), 1023–1032.

Triandis, H. C. (1993). Collectivism and individualism as cultural syndromes. *Cross-Cultural Research*, *27*(3–4), 155–180.

Vandello, J. A., & Cohen, D. (1999). Patterns of individualism and collectivism across the United States. *Journal of Personality and Social Psychology*, *77*(2), 279–292.

Van de Vliert, E. (2008). *Climate, affluence, and culture*. Cambridge University Press.

Wei, J., Fan, L., Zhang, Y., Li, S., Partridge, J., Claytor, L., & Sulo, S. (2018). Association between malnutrition and depression among community-dwelling older Chinese adults. *Asia-Pacific Journal of Public Health*, *30*(2), 107–117.

Welzel, C. (2013). *Freedom rising: Human empowerment and the quest for emancipation*. Cambridge University Press.

Wood, A., Rychlowska, M., & Niedenthal, P. M. (2016). Heterogeneity of long-history migration predicts emotion recognition accuracy. *Emotion*, *16*(4), 413–420.

Xie, Z., Lv, X., Hu, Y., Ma, W., Xie, H., Lin, K., Yu, X., & Wang, H. (2015). Development and validation of the geriatric depression inventory in chinese culture. *International Psychogeriatrics*, *27*(9), 1505–1511.

Zisberg, A. (2017). Anxiety and depression in older patients: The role of culture and acculturation. *International Journal for Equity in Health*, *16*(1), 177–177.