The effects of secondary stressors, social identity, and social support on perceived stress and resilience: Findings from the COVID-19 pandemic

Evangelos Ntontis[1*], Angélique M. Blackburn[2], Hyemin Han[3], Sabrina Stöckli[4], Taciano L. Milfont[5], Jarno Tuominen[6], Siobhán M. Griffin[7], Gözde Ikizer[8], Alma Jeftic[9], Stavroula Chrona[10], Aishath Nasheedha[11], Liudmila Liutsko[12], Sara Vestergren[13]

[1] School of Psychology and Counselling, The Open University, United Kingdom
[2] Department of Psychology and Communication, Texas A&M International University, United States of America
[3] Educational Psychology Program, University of Alabama, United States of America
[4] Department of Consumer Behavior, University of Bern, Switzerland; Department of Business Administration, University of Zurich, Switzerland
[5] School of Psychology, University of Waikato, New Zealand
[6] Department of Psychology and Speech-Language Pathology, University of Turku, Finland
[7] Department of Psychology, University of Limerick, Ireland
[8] Department of Psychology, TOBB University of Economics and Technology, Turkey
[9] Peace Research Institute, International Christian University, Japan
[10] Department of Politics, School of Law, Politics and Sociology, University of Sussex
[11] Villa College, Maldives
[12] The Barcelona Institute for Global Health, ISGlobal, Barcelona, Spain & Lomonosov Moscow State University, Faculty of Psychology, Moscow, Russia
[13] School of Psychology, Keele University, United Kingdom

***Corresponding author:** Dr Evangelos Ntontis, School of Psychology & Counselling, The Open University, Gardiner 2, Walton Hall, Milton Keynes, UK, MK7 6AA, evangelos.ntontis@open.ac.uk

Conflict of Interests: The authors declare that there are no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Author ORCID Profiles
Evangelos Ntontis https://orcid.org/0000-0001-8284-6015
Angélique M. Blackburn https://orcid.org/0000-0001-5378-3932
Hyemin Han https://orcid.org/0000-0001-7181-2565
Sabrina Stöckli https://orcid.org/0000-0002-8322-2906
Taciano L. Milfont https://orcid.org/0000-0001-6838-6307
Jarno Tuominen https://orcid.org/0000-0002-3892-3199
Siobhán M. Griffin https://orcid.org/0000-0002-3613-2844
Gözde Ikizer https://orcid.org/0000-0003-3567-5991
Alma Jeftić https://orcid.org/0000-0002-9285-2061
Stavroula Chrona https://orcid.org/0000-0002-0914-4938
Aishath Nasheeda https://orcid.org/0000-0001-6419-2599
Liudmila Liutsko https://orcid.org/0000-0002-2569-0760
Sara Vestergren https://orcid.org/0000-0003-0514-6749

Statement of Contributions

All authors contributed to the study conception, design, and data collection. Project administration was conducted by S.V., E.N, A.M.B., and H.H. Formal analyses were performed by H.H., T.M., and S.S. The first draft of the manuscript was written by E.N., A.M.B., and H.H. The manuscript was revised and edited by E.N., A.M.B., H.H., S.S., T.L.M., G.I., S.C., A.N., L.L., S.M.G, A.J., J.T. & S.V. All authors read and approved the final manuscript.

The data analysis was pre-registered (https://doi.org/10.17605/OSF.IO/C3JVW). The dataset analysed during the current study are available in the Open Science Framework repository: Vestergren & COVIDiSTRESS II Consortium, 2021. COVIDiSTRESS II Global Survey (https://osf.io/36tsd/). All relevant source code files are available via GitHub (https://github.com/hyemin-han/COVIDiSTRESS2_Stress). This article was supported by a Texas A&M International University (TAMIU) Research Grant. The authors would like to acknowledge the contributions of friends and collaborators in translating and sharing the COVIDiSTRESS survey, as well as the study participants.

Acknowledgments

We would like to thank Anna Morf for her support in proofreading the final manuscript, as well as the editor and the three anonymous reviewers for their very helpful comments in earlier drafts of this manuscript.

Abstract

Primary stressors are direct outcomes of extreme events (e.g., viruses, floodwater) whereas secondary stressors stem from pre-disaster life circumstances and societal arrangements (e.g., illness, problematic pre-disaster policies) or from inefficient responses to the extreme event. Secondary stressors can cause significant long-term damage to people affected but are also tractable and amenable to change. In this study we explored the association between secondary stressors, social identity processes, social support, and perceived stress and resilience. Pre-registered analyses of data from the COVIDiSTRESS Global Survey Round II (N = 14,600; 43 countries) show that secondary stressors are positively associated with perceived stress and negatively associated with resilience, even when controlling for the effects of primary stressors. Being a woman or having lower socioeconomic status (SES) is associated with higher exposure to secondary stressors, higher perceived stress, and lower resilience. Importantly, social identification is positively associated with expected support and with increased resilience and lower perceived stress. However, neither gender, SES, or social identification moderated the relationship between secondary stressors and perceived stress and resilience. In conclusion, systemic reforms and the availability of social support are paramount to reducing the effects of secondary stressors.

Keywords: COVID-19; primary stressors; resilience; secondary stressors; social identity; stress; social support

Introduction

Extreme events and major incidents can have a dramatic impact on people's lives and affect their physical and psychological wellbeing in multiple ways. Sometimes the stressors that people experience are inherent in the events themselves (e.g., viruses, floodwaters, earthquakes, fires, mass displacement) and are called *primary stressors*. In other cases, the stressors originate not in the events themselves but in people's life circumstances before an extreme event (e.g., illness), in pre-disaster social factors and societal arrangements (e.g., work circumstances, bureaucracy), or in problematic and inefficient responses to the extreme event itself (e.g., lack of governmental support). These stressors are called *secondary stressors* (Williams et al., 2021). To overcome both types of stressors, the availability and provision of social support towards those in need is paramount (Kaniasty & Norris, 1999), often mobilised through fellow group members (Haslam et al., 2012).

In this pre-registered study, we focus on the relationship between stressors, social identity processes, expected support, and people's perceived stress and resilience. We use data from the COVIDiSTRESS Global Survey Round II (Blackburn et al., 2022; Vestergren & COVIDiSTRESSII Collaboration, 2021), which included 14,600 participants from 43 countries.

Distress and stressors in extreme events

The experience of distress is common during extreme events (Williams et al., 2014). Distress refers to overwhelming and negative "*experiences and feelings of people after external events that challenge their tolerance and adaptation*" (Department of Health, 2009, p. 20) and can manifest at behavioural, psychological, or physiological levels. However, negative experiences or functional impairment caused by extreme events are often transient, expected, and should not be confused with the presence of mental health disorders (Department of Health, 2009; Williams et al., 2014). The majority of those affected often cope well in extreme events without developing psychopathology, and although substantial numbers of the population experience some levels of psychological impairment, they gradually recover. Only a small proportion develop mental health disorders (Department of Health, 2009; Goldmann & Galea, 2014; Norris et al., 2009). However, clear patterns of inequality characterise the impact of extreme events, with women and people of lower SES being more adversely affected by exposure to such extreme situations (Norris et al., 2002). This is due to societal inequalities that predate the extreme event, whose vicious effects carry over into the disaster period and exacerbate any negative outcomes of exposure.

Distress and other negative mental health experiences in disasters are caused by stressors. Stressors refer to circumstances, attitudes, responses, and events that can trigger distress responses in those affected, or which can cause tension due to being perceived as excessive by those affected (Stokols, 1985). As noted above, stressors can be conceptualised as belonging in two categories (Lock et al., 2012; Williams et al., 2021). *Primary stressors* are "*inherent in particular major incidents, disasters, and emergencies and arising directly from those events*" (Department of Health, 2009, p. 20) and include issues such as direct exposure to the extreme event itself, experiencing or witnessing death, injury, or gruesome scenes. *Secondary stressors* on the other hand have been defined as "*1. Social factors and people's life circumstances (including the policies, practices, and social, organisational, and financial arrangements) that exist prior to an incident or emergency, but which impact them during that major incident, emergency, disaster, conflict, or disease outbreak, and/or 2. Societal responses to the major incident or emergenc*y" (Williams et al., 2021, p. 6). Hence, secondary stressors refer to personal and structural circumstances that either pre-date the extreme event or appear during and shortly after the extreme event due to inefficient or problematic societal responses to it. Typical examples include breakdown of social relationships (e.g., filial, family, organisational), lack of leadership, lack of social support or information, or difficulties in claiming financial compensation. The term ‘secondary’ does not connote lesser importance but signifies stressors that are not direct outcomes of the extreme event itself but stem from the structure of people’s socio-political environments (Williams et al., 2021).

Secondary stressors are associated with distress. For example, following hurricane Katrina, secondary stressors such as separation from one’s family, emergence of financial problems, and lack of financial support grants were related to mental health issues that persisted even 32 months later (Picou & Hudson, 2010). In the case of flooding, secondary stressors include issues like difficulties in claiming insurance compensation, relationship problems, disruption to work and education, loss of support structures, loss of sentimental items, and loss of access to healthcare services and social activities (Mulchandani et al., 2019; Tempest et al., 2017; Waite et al., 2017). The significance of secondary stressors lies in the effects they exert on a constant basis, often over extended periods of time. For example, Norris and Uhl (1993) showed that the acute effects of disasters (e.g., loss, injury, life threat) on psychological distress were mediated by chronic stressors (e.g., financial issues, filial burdens, or marital strains). Such stressors are rooted in the social environments and institutionalised roles that people can find themselves in, the endurance of which can lead to the potential chronicity of distress (Pearlin, 1989). Thus, the persistence of secondary stressors can render distress chronic, potentially leading to persistent dysfunction (Norris et al., 2002, 2009).

Based on the above, a focus on secondary stressors is paramount for several reasons. As Williams et al. (2021) emphasise, such a focus can expand our thinking on the effects of disasters beyond the narrower scope of mental health and its symptomatology, shifting it towards the structure of the social environments and how they contribute to the experience of trauma instead. Further, it accounts for both pre- and peri-disasters’ personal, social, and structural conditions and considers how those factors interact with the extreme event itself to exacerbate trauma. Third, if secondary stressors are predominantly elements of the social and political environment and systemic in nature, then they are tractable and amenable to change. This realisation forces us to move beyond individualised approaches to tackling them and consider systemic changes as remedies to their negative effects and for ways to better prepare for future events.

Psychosocial sources of resilience: groups, identity, and social support

People can demonstrate remarkable resilience to extreme events, with many people experiencing either no symptoms or mild, non-pathological distress and will eventually return to normality (Department of Health, 2009; Goldmann & Galea, 2014; Norris et al., 2009). A tendency to ‘bounce-back’ is often termed resilience. Resilience does not reflect the absence of or resistance to short-term distress (which is expected during extreme events) but rather denotes the ability to bounce back and recover (Kuldas & Foody, 2022; Leys et al., 2020; Smith et al., 2008). For Kuldas and Foody (2022), resilience is not a stable trait but can be conceptualised as a dynamic process and outcome that stems from people’s interactions with their environments, their effective use of individual capacities and social resources, and their capacity to transform their environments (also see Norris et al., 2009; Williams et al., 2014). Two such adaptive capacities are the availability of social support and feeling oneself as part of a larger group or collective, namely social identification (Williams et al., 2014).

Social support is defined as “*those social interactions or relationships that provide individuals with actual assistance or that embed individuals within a social system believed to provide love, caring, or sense of attachment to a valued social group or dyad*” (Hobfall, 1988, p. 121). Social support can often be practical (e.g., tools, money, food), emotional (e.g., compassion, care), or informational (e.g., advice, guidance) (Kaniasty & Norris, 1999; Norris & Kaniasty, 1996). At the onset of extreme events, there is often an emergent sense of community and the mobilisation of solidarity and social support (Drury et al., 2019; Fritz, 1965/1996; Quarantelli, 1999). Findings from the early stages of the pandemic highlight that people's sense of community increased (Sibley et al., 2020). However, these elements are often short-lived (Kaniasty & Norris, 1999; Ntontis et al., 2020, 2022; Quarantelli, 1999). Reduction in people's expectations of social support can often be traumatic (Norris & Kaniasty, 1996), but receiving support can increase people's perceptions of its availability and thus improve psychological wellbeing (Norris & Kaniasty, 1996). Nevertheless, social support is not equally distributed, and a clear pattern of neglect is often observed in how communities respond to extreme events and in terms of who is supported. For example, inequalities in terms of ethnicity or SES led to minority groups or those who are less affluent to receive less social support from their communities (Kaniasty & Norris, 1995).

The mobilisation of social support and perceptions of its availability are often an outcome of social identity processes (Haslam et al., 2018). When people perceive themselves as group members vis-à-vis other group members, various positive behavioural, relational, and cognitive changes can manifest. For example, people experience a sense of belonging to a wider collective, expect to be supported by fellow group members, and often demonstrate improved wellbeing (Haslam et al., 2018). At the onset of COVID-19, social identity was associated with less anxiety, increased mental wellbeing, and providing more social support (Vignoles et al., 2021). Findings from bombings, earthquakes, and flooding demonstrate the positive influence of shared social identity on both behaviour and cognition, with survivors feeling an emergent sense of togetherness at the onset of the extreme event, reporting receiving support and expecting to be supported by fellow ingroup members, coordinating their activities more efficiently, and experiencing a sense of collective efficacy and increased wellbeing (e.g., Drury et al., 2016, 2019; Ntontis et al., 2020, 2021; Stancombe et al., 2022).

The present study

To date there is a lack of research on the impact of secondary stressors in the context of pandemics. Considering that pandemics often have long lasting effects that impact all areas of personal and social life, the presence of secondary stressors can lead to distress and the potential development of mental health issues. At the same time, research shows that social support and social identity are implicated in lower levels of distress in those affected. However, the interaction between secondary stressors, social identity, and expected social support is yet to be explored. Our general aim in this paper is to examine the association of primary and secondary stressors, social identity processes, expected social support, and perceived stress and resilience (Figure 1).

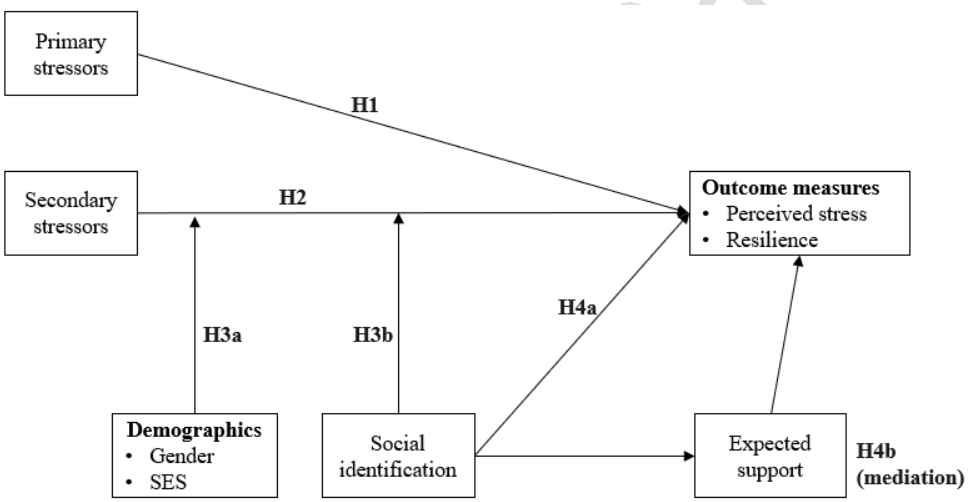
First, direct exposure to extreme events themselves has been shown to be associated with reduced psychological wellbeing (Norris et al., 2002). Thus, our first hypothesis proposed that primary stressors would be positively associated with perceived stress and negatively associated with resilience (H1).

Second, the existing literature has highlighted that secondary stressors are associated with reduced wellbeing in those affected (Norris et al., 2002; Williams et al., 2021). This is because extreme events do not occur in a social vacuum, and their effects can be exacerbated or prolonged depending on the contextual circumstances and social organisation of the lives of individuals and of the communities affected. Secondary stressors acquire 'a life of their own' and exert their impacts independently even when the primary stressors (e.g., floodwaters) have receded. Based on this strand of the literature, we proposed that secondary stressors would be positively associated with perceived stress and negatively associated with resilience, over and above the effects of primary stressors (H2).

Third, considering patterns of inequality in the context of disasters (e.g., Kaniasty & Norris, 1995; Norris et al., 2002), we hypothesised that the association between secondary stressors and perceived stress and resilience would be moderated by demographic characteristics, and particularly gender and SES. We predicted (H3a) that the association between secondary stressors and the outcome variables would be greater (i.e., higher perceived stress and lower resilience) for demographic characteristics mostly affected by inequality such as being a woman or having lower SES (Norris et al., 2002). At the same time, considering the protective effects of group belonging in general (e.g., Haslam et al., 2018) and in the context of extreme events more specifically (Ntontis et al., 2021), we also predicted that the association between secondary stressors and the outcome variables would be moderated by social identification (H3b) in that it would be lower for people reporting higher levels of social identification.

Fourth, considering the protective effects of group belonging in terms of enhancing wellbeing but also its association with increased expectations of support (Haslam et al., 2018; Ntontis et al., 2021), we hypothesised that higher levels of social identification would be associated with lower levels of perceived stress and higher levels of resilience (H4a), and that the aforementioned relationship would be mediated by expected support (H4b).

Figure 1. *Pre-registered hypotheses regarding the relationships between primary and secondary stressors, social identity processes, perceived stress, and resilience, including potential mediators and moderators. Hypotheses were tested individually.*



Method

Data collection

We analysed data from the COVIDiSTRESS Global Survey Round II (Blackburn et al., 2022; Vestergren & COVIDiSTRESSII Collaboration, 2021). This was a cross-sectional survey study based on the COVIDiSTRESS II Global Survey, distributed globally online between May 28th and August 29th, 2021. Data collection and analysis procedures for this multi-part research project were pre-registered before data collection began (https://osf.io/pg3h8) and have been reported in greater detail elsewhere (see Blackburn et al., 2022). In this study we only report analyses related to the relationship between stressors, perceived stress and resilience, and social identity and social support processes. All analyses related to this specific study were registered before the analysis procedure started (https://osf.io/c3jvw). For transparency, additional exploratory analyses are justified and reported in a separate section. Ethical approval was provided by the University of Salford.

Data cleaning was conducted prior to this analysis and is also reported in detail elsewhere (Blackburn et al., 2022). In short, we excluded test cases and those accessed through a preview link, those that lacked consent, those in which the respondent failed the attention check, and those in which survey completion was less than three minutes. Then data was recoded to align with the original scoring in previous studies (e.g., the Perceived Stress Scale was recoded to a scale from 0–4).

After data cleaning, there were 15,740 participants in the dataset, recruited from a total of 121 countries and 48 language groups (10,558 women [67.08%], 5,009 men [31.82%], 163 other [1.04%], 10 unknown [.06%]). While conducting measurement invariance testing and alignment, responses from language groups where 100 or more participants completed the survey were analysed (N = 15,103 across 28 language groups; 10,152 women [67.22%], 4,788 men [31.70%], 153 other [1.01%], 10 unknown [.07%]) as suggested in prior studies using the same approach (e.g., Han, 2022). Then, we included responses collected from countries where at least 30 participants completed the survey to detect both the effects of individual- and country-level predictors to improve convergence for multilevel modelling-based analyses (e.g., Lieberoth et al., 2021). After conducting invariance testing and filtering procedures, we analysed the final dataset containing responses from 14,600 participants from 43 countries (9,860 women [67.53%], 4,598 men [31.49%], 137 other [.94%], 5 unknown [.03%], M age = 36.54, SD age = 14.47): Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Colombia, Costa Rica, Czech Republic, Denmark, Ecuador, Estonia, Finland, Germany, Guatemala, Honduras, Hong Kong (S.A.R.), Ireland, Italy, Japan, Kazakhstan, Kyrgyzstan, Lebanon, Malaysia, Maldives, Nepal, New Zealand, Norway, Other, Pakistan, Portugal, Russian Federation, Slovakia, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, Uganda, Ukraine, United Kingdom of Great Britain and Northern Ireland, United States of America, and Uruguay. A brief demographics description of participants (i.e., age, gender, education level) in each country is presented in an online supplementary table available on our GitHub repository (https://github.com/hyemin-han/COVIDiSTRESS2_Stress/blob/main/R1/Demographics.csv).

Measures

A full list of the variables included in the overall survey is available at OSF (https://osf.io/gcek7/); this document outlines all survey items and the response options. For all variables, neutral options were treated as midpoints on the scale. For the purposes of this analysis, we included measures of primary stressors, secondary stressors, expected support, social identification, demographics, perceived stress, resilience, gender, and SES.

Primary stressor (Cronbach's $\alpha = .68$) and secondary stressor (Cronbach's $\alpha = .72$) items were adapted from Norris and Uhl (1993). Each scale includes 4 items rated on from 0 (*not at all concerned*) to 4 (*extremely concerned*), with a NA (Not Applicable) option. Examples of primary stressors include concerns about participants or other people close to them catching COVID-19 or being unable to travel. Examples of secondary stressors include concerns about participants not being able to find a job in the future, having inadequate support from the government or their employer, their relationship or marriage breaking down, about their children’s education, or not having access to healthcare. These items were administered to all participants.

Expected support (Cronbach's $\alpha = .86$) measured the degree to which individuals feel that they can turn to others for help and support when needed (e.g., I can count on others to meet my needs if things go wrong). The scale contains 3 items rated from 1 (*strongly disagree*) to 7 (*strongly agree*) adapted from Ntontis et al. (2021).

A social identification scale (Cronbach's α = .71) was adapted from Postmes et al. (2013) to measure the degree to which individuals identify with their family, local community, country, and humanity (e.g.,I identify with people in my local community), with 4 items rated from 1 (*strongly disagree*) to 7 (*strongly agree*) .

The Perceived Stress Scale (Cohen et al., 1983) is a 10-item measure of perceived stress, assessing perceptions of unpredictability, uncontrollability, and overloading experienced during the previous month (Cronbach's α = .87). The scale has been used in pandemic research (Lieberoth et al., 2021). Items were rated from 0 (*never*) to 4 (*very often*) and for example ask people about the extent to which they "felt nervous and stressed".

The Brief Resilience Scale (Smith et al., 2008; Cronbach's α = .87) contains 5 items rated from 1 (*strongly disagree*) to 7 (*strongly agree*) which assess the ability to overcome difficulty (e.g., "It does not take me long to recover from a stressful event"). Rather than measuring the factors and resources that make resilience possible, the scale measures the quality and perceived ability of being able to bounce back following stress (Smith et al., 2008).

Data on gender was collected by asking participants to select the option that best represented them (i.e., women, men, or other/would rather not say). To assess participants' socioeconomic status, we used an adapted MacArthur Scale of Subjective Social Status (Adler et al., 2000; Goodman et al., 2001) which asks participants to position themselves or their family in a ladder. The top of the ladder corresponds to the people with the most resources, whereas the bottom refers to people with the least resources.

Data analysis procedure

Because our measures were translated into different languages, an examination of measurement invariance was required, or tests to check whether participants from all countries had completed the measures similarly (Chen & West, 2008; Milfont & Fischer, 2010). Thus, we first conducted measurement invariance tests across different language groups to assure that scales presented in different languages measured constructs of interest consistently. Because the required level of equivalence was not supported via the traditional invariance testing, we used the alignment method. Measurement alignment is a way to compare latent means across different groups even when invariance is not supported by adjusting factor loadings and intercepts in each group (Muthén & Asparouhov, 2018). Further technical details about the measurement invariance testing, measurement alignment, and hypothesis testing are described in Supplementary Methods. For a detailed analysis plan, see our pre-registration (https://osf.io/c3jvw).

Results

Descriptive statistics

Detailed descriptive statistics for each country are presented in Table S1. A correlation matrix appears in Table 1 below.

Table 1. *Correlation between variables of interest*

	1	2	3	4	5
1. Primary stressor	-				
2. Secondary stressor	.38	-			
3. Expected support	.03	-.21	-		
4. Social identification	.07	-.14	.35	-	
5. Perceived stress	.28	.43	-.22	-.05	-
6. Resilience	-.13	-.28	.33	.23	-.50

Note. All correlation coefficients were significantly different from zero, $p < .001$ after false discovery rate correction (the default adjustment method set by *psych*, Holm adjustment, was applied). N ranges from 7,244 (correlation between secondary stressors and resilience) to 14,471 (correlation between expected support and perceived stress).

Measurement invariance testing

We conducted measurement invariance testing to examine whether our measurement models were equally valid across samples. Results from the traditional invariance testing approach indicated that scalar invariance was not supported in none of the scales used for this study (see Table S2). Thus, we performed measurement alignment to address measurement non-invariance. In all cases, the non-invariance was well absorbed through alignment given $R^2_{loadings}$ and $R^2_{intercepts}$ higher than .75 in all scales. Table S3 reports $R^2_{loadings}$ and $R^2_{intercepts}$ among the tested scales. In addition, as shown in Table S4, the repeated Monte Carlo simulations demonstrated that the alignment procedures were performed in a reliable and valid manner. Given that scalar invariance was not supported, and measurement alignment was able to address the non-invariance successfully, we used factor scores calculated with factor loadings and intercepts adjusted through measurement alignment to test our hypotheses.

Hypothesis testing

Assumption checks

Before testing our hypotheses, we examined whether the assumptions for linear regression were met. Multicolinearity was not an issue. First, in all cases, linearity assumptions were satisfied (see Figures S1-S2 for H1, Figures S3-S4 for H2, Figures S5-S6 for H3). Second, the maximum variance inflation factors did not exceed 1.4 in all hypothesis testings. Because 1.4 was significantly lower than the threshold determining the presence of significant multicolinearity, 3.0, we concluded that multicolinearity could not be an issue in our analysis.

Association between primary stressors, perceived stress and resilience

We examined whether primary stressors significantly predicted perceived stress and resilience (H1). The Bayesian MLM indicated that the model with random intercepts and slopes best predicted perceived stress (see column H1 in Table S5 for model comparison). One caveat is that when resilience was predicted, although M2 (model with fixed effects, random slopes and intercepts) demonstrated the highest model BF, it was not significantly more strongly supported compared with M1 (model with fixed effects and random intercepts). Because the resultant ICCs of both models were below .25, we compared the best models with the models without random effects. In both outcome variables, models with random effects were significantly better than the models without the effects in terms of model BFs (see Table S5). Furthermore, the sensitivity test indicated that the hypothesis testing results were robust since use of the alternative prior did not alter the results.

Both the positive association of primary stressors with perceived stress and the negative association between primary stressors and resilience were very strongly supported by evidence as hypothesised (see Table 2 for estimated coefficients, 95% CIs, and effect sizes). Resultant effect sizes in terms of Cohen's *d* were also non-trivial (> .20). Thus, H1 was supported.

Table 2. *Hypothesis testing results (H1)*

				95% Bayesian CI					
	b	*SE*	BF (one-tailed)	Lower	Upper	*t*	*df*	*p*	Cohen's *d*
H1 (DV = perceived stress)									
Primary stressor	.23	.02	Infinite	.20	.26	13.69	35.27	< .001	.50
H1 (DV = resilience)									
Primary stressor	-.15	.02	Infinite	-.17	-.12	-8.93	30.45	< .001	-.29

Association between secondary stressors, perceived stress, and resilience

Regarding H2, the model predicting perceived stress with both random intercepts and slopes without interaction effects was found to be the best model (see column H2 in Table S5 for model comparison). The model predicting perceived stress reported ICCs lower than .25. Thus, we compared the best model with the models without random effects. As shown in Table S5, in all cases, models with random effects were significantly better than models without random effects, given model BFs. The sensitivity check indicated that the hypothesis testing results in terms of BFs did not significantly change even when the alternative prior was employed.

Table 3. *Hypothesis testing results (H2, H3a and H3b, dependent variable = perceived stress)*

	b	*SE*	BF (one-tailed)	95% Bayesian CI Lower	Upper	*t*	*df*	*p*	Cohen's *d*
H2 (DV = perceived stress)									
Secondary stressor	.36	.02	Infinite	.33	.40	18.88	38.74	< .001	.76
H3a (DV = perceived stress)									
Gender	-.19	.02	Infinite	-.22	-.15	-9.38	8,153.00	< .001	-.20
SES	-.10	.01	Infinite	-.11	-.08	-16.09	8,179.00	< .001	-.37
H3b (DV = perceived stress)									
Secondary stressor	.31	.02	Infinite	.28	.34	19.11	38.50	< .001	.76
Social identification	-.08	.02	Infinite	-.11	-.06	-5.95	18.90	< .001	-.13
Interaction	.01	.01	.23	-.01	.02	.08	1,661.00	.44	.03

Secondary stressors were significantly associated with perceived stress (see H2 in Table 3 for estimated coefficients, 95% CIs, and effect sizes). When the model which included interaction effects with demographics (A) was compared with the aforementioned best model (B), model BFAB, BFAB = .00, indicated that the model with only the main effects was significantly better (H3a). Even when each demographic variable was examined individually, none of the tested models was significantly better than the model with just the main effects. The model BF was zero for the models calculated with the interaction effects with gender, education, and employment unlike hypothesised. We explored the main effects of gender and SES in the tested model with perceived stress as an outcome variable. Initially, we intended to examine education and employment as demographic variables indicating SES. However, because of difficulties in analysis and interpretation due to the categorical nature of those variables and the use of multiple categories (and in our case, from different and very diverse countries), we ended up employing the MacArthur Scale of Subjective Social Status as an indicator of SES, which is also assumed to be closely associated with educational background and employment status, for the additional analysis. Analysis indicated negative main effects for both gender and SES on perceived stress, indicating that women and those with lower SES reported higher perceived stress levels (see H3a in Table 3 for estimated coefficients, 95% CIs, and effect sizes).

Moreover, when the interaction between secondary stressors and social identification was included in the models predicting perceived stress, the interaction model (A) was significantly better supported by evidence compared with the model including only the main effect of secondary stressors (B), log(BFAB) = 99.89, as hypothesised (H3b). Both the positive main effect of secondary stressors and negative main effect of social identification were statistically significant. However, the interaction effect was inconclusive (see H3b in Table 3 for estimated coefficients, 95% CIs, and effect sizes).

Overall, secondary stressors were significantly and positively associated with perceived stress, and H2 was supported. Being a woman or having lower SES was also associated with higher levels of stress.

Higher levels of social identification were also associated with lower levels of perceived stress. However, neither demographics (SES, gender) nor social identification moderated the relationship between secondary stressors and perceived stress, so H3a and H3b were not supported.

Table 4. *Hypothesis testing results (H2, H3a, and H3b, dependent variable = resilience)*

				95% Bayesian CI					
	b	*SE*	BF (one-tailed)	Lower	Upper	*t*	*df*	*p*	Cohen's *d*
H2 (DV = resilience)									
Secondary stressors	-.22	.01	Infinite	-.24	-.19	-17.98	6,924.00	< .001	-.43
H3a (DV = resilience)									
Gender	.19	.02	Infinite	.14	.24	7.86	6,993.00	< .001	.19
SES	.09	.01	Infinite	.08	.11	12.95	7,010.00	< .001	.31
H3b (DV = resilience)									
Secondary stressors	-.18	.01	Infinite	-.20	-.17	-17.40	6,826.00	< .001	-.42
Social identification	.14	.01	Infinite	.12	.16	9.60	6,831.00	< .001	.23
Interaction	-.01	.01	.31	-.02	.01	-.71	6,959.00	.48	-.02

Turning now to resilience, the model only with main effects and random intercepts was found to be the best model (see column H2 in Table S5). The model predicting resilience reported ICCs lower than .25. Thus, we compared the best model with the models without random effects. As shown in Table S5, in all cases, the models with random effects were significantly better than the models without random effects given model BFs. The sensitivity check indicated that the hypothesis testing results in terms of BFs did not significantly change even when the alternative prior was employed.

The negative main effect of secondary stressors on resilience was significant, and H2 was confirmed (see H2 in Table 4 for estimated coefficients, 95% CIs, and effect sizes). When the model with only the main effects (B) was compared with the model with the interaction effects with demographics (A), model BF indicated that the main effect-only model was significantly better, BFAB = .00 (H3a). Similar to results with perceived stress, the addition of each individual interaction effect did not significantly improve the prediction model. When the interaction effect with gender, education and employment was added, the interaction model (A) was inferior to the model only with main effects (B) unlike hypothesised (BFAB = .00 for all). We also explored the main effects of gender and SES on resilience. Similar to the case of the main effect analysis of perceived stress, we employed SES in lieu of education and employment for the current analysis. Both main effects of gender and SES were significant, indicating that women and those with lower SES reported lower resilience (see H3a in Table 4 for estimated coefficients, 95% CIs, and effect sizes). Furthermore, when the model with interaction effect between secondary stressors and social identification (B) was compared with the main-effect only model (A), the model with the interaction effect was superior, log(BFAB) = 123.31 (H3b). Both the negative main effect of secondary stressors and the positive main effect of social identification were significant in line with prediction. However, the interaction effect was not conclusively supported by evidence (see H3b in Table 4 for estimated coefficients, 95% CIs, and effect sizes).

Overall, similar to the previous outcome variable, perceived stress, secondary stressors were significantly and negatively associated with resilience, and H2 was supported. Being a woman or having lower SES was associated with lower levels of resilience, whereas higher levels of social identification were associated with higher levels of resilience. However, neither demographics (SES, gender) nor social identification moderated the relationship between secondary stressors and resilience, so H3a and H3b were not supported.

Expected support mediates the relationship between social identification and perceived stress and resilience

We examined whether social identification was associated with decreased perceived stress and increased resilience (H4a) and whether this association was significantly mediated by expected support (H4b). Starting with perceived stress, model BFs indicated that the model with both random intercepts and slopes was the best model (see column H4a in Table S5). For this mediation analysis, the sensitivity test indicated that employment of the alternative prior did not alter the hypothesis testing results.

Social identification was positively associated with expected support, and the latter was negatively associated with perceived stress (see H4a (DV = perceived stress) in Table 5 for estimated coefficients, 95% CIs, and effect sizes). Notably, the indirect effect did not include zero, supporting our hypothesis that expected support mediated the relationship between social identification and perceived stress. Of the total effect estimated 54.88% was mediated (see Table 6).

Table 5. *Hypothesis testing results (H4a and H4b)*

	b	*SE*	BF (one-tailed)	95% Bayesian CI Lower	95% Bayesian CI Upper	*t*	*df*	*p*	Cohen's *d*
H4a (DV = perceived stress)									
Social identification	-.31	.02	Infinite	-.34	-.28	-17.99	22.26	<.001	-.64
Expected support	-.05	.02	Infinite	-.08	-.02	-3.74	36.63	.001	-.05
(H4b) Social identification → Expected support	.20	.01	Infinite	.18	.22	15.04	18.64	<.001	.40
H4a (DV = resilience)									
Social identification	.10	.02	Infinite	.07	.12	7.43	35.68	<.001	.16
Expected support	.25	.02	Infinite	.22	.28	12.72	27.04	<.001	.50
(H4b) Social identification → Expected support	.20	.01	Infinite	.18	.22	15.04	18.64	<.001	.40

When resilience was examined (H4a and H4b), we found that the mediation model including both random intercepts and slopes reported was the best although it was not decisively better than the model only with random intercepts (see column H4a in Table S5). For the mediation analysis focusing on resilience, the sensitivity test indicated that employment of the alternative prior did not alter the hypothesis testing results.

When this model was examined, the estimated effects supported our predictions. Resilience was positively associated with both social identification and expected support. Social identification and expected support were positively associated as well (see subsection H4a (DV = resilience) in Table 5 for estimated coefficients, 95% CIs, and effect sizes). Importantly, the indirect effect did not include zero and supported our hypothesis that expected support would mediate the relationship between social identification and resilience. Of the total effect, 33.80% was mediated (see Table 6).

Table 6. *Mediation analysis results (H4b)*

	DV = perceived stress			DV = resilience		
		95% CI			95% CI	
	Estimated	Lower	Upper	Estimated	Lower	Upper
Direct effect (ADE)	-.05	-.08	-.02	.10	.07	.13
Indirect effect (ACME)	-.06	-.07	-.05	.05	.04	.06
Mediator effect	-.31	-.35	-.28	.25	.21	.29
Total effect	-.11	-.15	-.08	.15	.11	.18
% mediated	54.88%	38.39%	71.36%	33.80%	24.66%	42.93%

These results indicate that higher levels of social identification are associated with lower perceived stress and higher resilience, and that expected support is one mechanism that helps explain these associations.

Additionally, we examined whether the tested relationships between secondary stressors, social identification, expected support, and our outcome variables were influenced by potential false positives possibly emerging from measurement errors (Westfall & Yarkoni, 2016). In a supplementary test (see Supplementary Results), we found that measurement errors and inflated false positives were not an issue in our analyses, so the findings from the conducted analyses are deemed credible.

Additional exploratory analyses

Secondary stressors as mediating the relationship between demographic characteristics and perceived stress and resilience. Results from H3a showed that, despite identifying no interaction effects of gender and SES on the relationship between secondary stressors and our outcome variables, those demographic factors still exerted main effects. In an additional exploratory analysis, we examined whether the association between gender and SES (the predictors) and perceived stress and resilience (the outcome variables) was mediated by secondary stressors. That is, do secondary stressors help explain why people who might experience higher inequality than others (i.e., women and people with a lower SES) also experience increased perceived stress and decreased resilience? The mediation analysis was conducted with Bayesian MLM similar to how H4a and H4b were tested (also see Tables S9-S11).

Table 7. *Model comparisons for the exploratory mediation analysis*

log Model BF	Perceived stress	Resilience
M1 vs. M0	1,961.46	1,192.11
M2 vs. M0	1,961.48	1,192.15
M2 vs. M1	.02	.04
Examined Best model	M2	M2

Note. M0: model only with random effects. M1: model with fixed effects and random intercepts. M2: model with fixed effects, random slopes and intercepts.

First, we examined whether secondary stressors mediated the relationship between gender, SES and perceived stress. We compared the null, random intercept, and random slope models and found the model BF of the random slope model was highest although the model was not decisively better than the random intercept model (see Table 7). All examined paths were significant in the tested model (see Table 8 for estimated coefficients, 95% CIs, and effect sizes. Furthermore, in all cases, we found a significant non-zero mediation effect (see Table 9).

Table 8. *Results of the significance tests of the model paths*

				95% Bayesian CI	
	b	*SE*	BF (one-tailed)	Lower	Upper
DV = perceived stress					
Gender	-.20	.02	Infinite	-.23	-.16
SES	-.10	.01	Infinite	-.11	-.09
Secondary stressors	.35	.01	Infinite	.34	.37
Gender → Secondary stressors	-.13	.02	Infinite	-.17	-.10
SES → Secondary stressors	-.17	.01	Infinite	-.18	-.16
DV = resilience					
Gender	.20	.02	Infinite	.16	.24
SES	.10	.01	Infinite	.09	.11
Secondary stressors	-.23	.01	Infinite	-.25	-.21
Gender → Secondary stressors	-.14	.02	Infinite	-.17	-.10
SES → Secondary stressors	-.17	.01	Infinite	-.18	-.16

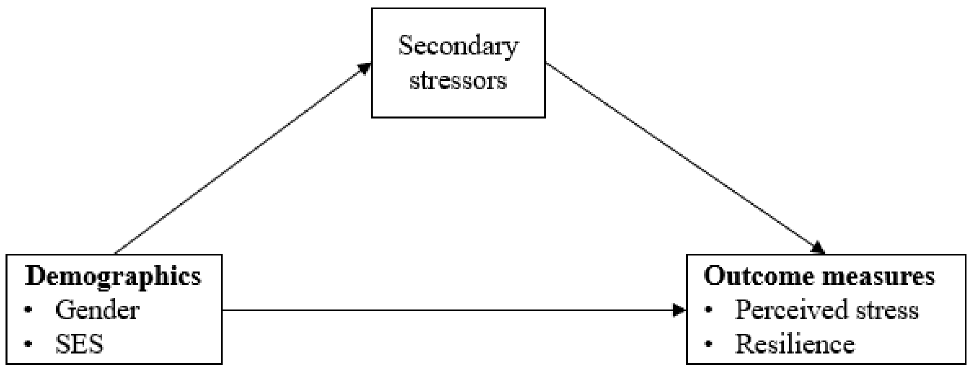
Second, we tested whether the association between gender, SES and resilience was mediated by secondary stressors. The same trends were found in this case as well. The random slope model was found to be the best although it was not decisively superior to the random intercept model (see Table 7). In the model, we found that all paths were significant (see Table 8 for estimated coefficients, 95% CIs, and effect sizes) and all mediation effects were non-zero (see Table 9).

Table 9. *Exploratory mediation analysis results*

	DV = perceived stress			DV = resilience		
	Treatment = gender (man)			Treatment = gender (man)		
		95% CI			95% CI	
	Estimated	Lower	Upper	Estimated	Lower	Upper
Direct effect (ADE)	-.20	-.23	-.16	-.10	-.11	-.09
Indirect effect (ACME)	-.05	-.06	-.03	-.06	-.07	-.06
Mediator effect	.36	.34	.37	.36	.34	.37
Total effect	-.24	-.28	-.20	-.16	-.18	-.15
% mediated	19.34%	13.25%	25.43%	37.94%	34.23%	41.65%
	Treatment = SES			Treatment =SES		
		95% CI			95% CI	
	Estimated	Lower	Upper	Estimated	Lower	Upper
Direct effect (ADE)	.20	.15	.25	.10	.08	.11
Indirect effect (ACME)	.03	.02	.04	.04	.03	.04
Mediator effect	-.23	-.25	-.20	-.23	-.25	-.20
Total effect	.23	.18	.28	.14	.12	.15
% mediated	13.20%	8.04%	18.36%	28.27%	23.98%	32.57%

These exploratory mediation analyses supported that secondary stressors help explain why women and those with lower SES experience more adverse psychological outcomes. In other words, women and people of lower SES experience higher perceived stress and lower resilience when compared to their counterparts, partially due to experiencing higher levels of secondary stressors (see Figure 2).

Figure 2. Secondary stressors as mediating the relationship between gender/SES and perceived stress and resilience



Testing all hypotheses in a single "global" model, with expected support as an additional moderator. Based on our pre-registration, each hypothesis was tested individually. However, testing one-on-one relationships between variables can potentially provide false positive results since controlling for potential confounding factors could be an issue (Chang, 1998). Hence, we tested one "global" model that included all the aforementioned hypothesised pathways. We did not include gender and SES as demographic moderators since the previously tested models with those variables were not found to be the best models (see H3a results). Furthermore, we also examined whether expected support moderated the relationship between stressors and perceived stress and resilience[1]. The global model was similarly tested with *brms*. Results from the "global" model are presented in Tables S6 and S7, and in Figure S9. In the case of predicting perceived stress, the model including all random effects was the best model, log(BF[M2vsM01]) = 5,144.85. When resilience was predicted, the model including random intercepts was the best, log(BF[M1vsM0]) = 4,009.52. Overall, even when all predictors and hypotheses were considered together (rather than based on individual hypothesis testing), the results were identical to previous individual tests for each hypothesis. The moderating effects of social identification and expected support were not significant.

Discussion

In this paper we used data from participants from 43 countries to investigate the association of primary and secondary stressors with people's perceived stress and resilience. We were also interested in the roles of social identity processes and social support in reducing stress and increasing resilience.

Our first hypothesis, H1, was supported. Primary stressors were positively associated with perceived stress and negatively associated with resilience. These findings are in line with previous empirical evidence showing how exposure to the extreme event itself can be associated with reduced wellbeing (Goldmann & Galea, 2014; Norris et al., 2002). Findings from the early stages of the COVID-19 pandemic similarly showed an increased prevalence of distress partially due to the threat of infection or the presence of symptoms (Gómez-Salgado et al., 2020).

However, in our analysis we went beyond the psychological impact of exposure to COVID-19 itself. Regarding our second hypothesis, H2, results showed that secondary stressors were positively associated with perceived stress and negatively associated with resilience even when controlling for the effects of

[1] This additional hypothesis was added following a recommendation from the anonymous reviewers.

primary stressors. Thus, social and systemic factors (e.g., relationship problems, lack of workplace support, childcare concerns) are associated with additional perceived stress on top of exposure to the extreme event itself. These findings are in line with the existing literature. Mulchandani et al. (2019) showed for example that people facing problems with post-disaster insurance policies exhibited elevated odds of reporting symptoms of anxiety, depression, and post-traumatic stress disorder, and Tempest et al. (2017) demonstrated that relationship problems, concerns about pets and health, or loss of sentimental items predicted psychological morbidity. Thus, considering the structure of the society and of people's social environments is paramount in reducing the negative effects of extreme events.

It was this focus on societal factors and their psychological impact following extreme events that motivated us to explore whether gender and SES modify the effects of secondary stressors on stress and resilience (H3a). In other words, are there any characteristics that can make certain people more susceptible to secondary stressors? Women, minority groups, and less affluent people are more affected by exposure to disasters and to their subsequent long-term impacts (Kaniasty & Norris, 1995, 1999; Norris et al., 2002) mainly due to pre-disaster patterns of inequality that carry well into the extreme event itself. However, in our case H3a was not empirically supported. That is, neither gender or SES moderated the relationship between secondary stressors and the two outcome variables. This possibly indicates that the experience of secondary stressors was associated with increased stress and decreased resilience regardless of participants' gender or SES. The absence of moderating effects is possibly associated with the nature of the stressors that we measured in the context of our study (e.g., lack of government or employer support, worrying about children's education). In cases of stressors like those measured, people's demographic characteristics might not be strongly associated with perceived stress and resilience, particularly 18 months since the emergence of the pandemic. However, the lack of baseline measures makes it impossible to make any safe statements regarding the influence of the aforementioned variables over time.

Despite the absence of moderating effects, there were statistically significant main effects of gender and SES on perceived stress and resilience. In line with the previous literature (e.g., Norris et al., 2002), women and less affluent people reported reduced psychological wellbeing compared to men and more affluent people, pointing us once again to the negative effects of patterns of inequality on health and wellbeing. Additional exploratory analyses influenced by previous findings showed that gender and SES were associated with higher perceived stress and lower resilience, with women and less affluent people reporting that they experienced higher levels of stressors. Thus, despite a 'global' association of secondary stressors with perceived stress and resilience being evident in our sample, patterns of inequality on the basis of SES and gender mean that particular stressors tied to those demographics (i.e., outcomes of an unequal societal structure based on gender discrimination and social roles and/or expectations, or stressors inherent in poorer households such as lack of access to resources and support) might make those affected particularly vulnerable and lead to the chronicity of stress as long as such unequal social environments are maintained. Our findings complement those by Norris and Uhl (1993) who showed that the negative relationship between exposure to disaster and mental health was mediated by chronic stressors akin to the secondary stressors described in our study.

Social identification did not moderate the relationship between secondary stressors and our psychological outcomes either (H3b). This means that the association of secondary stressors and the outcome variables did not vary depending on people's social identification with others. This finding is not surprising, especially if we take into account a) that data for this study was collected 18 months after the onset of the pandemic, and b) findings from the existing literature which show that the emergent sense of togetherness that characterises the early stage of disasters dissipates over time (e.g., Kaniasty & Norris, 1999; Ntontis et al., 2020, 2022). However, once again, the lack of baseline measures from the period of the onset of the pandemic means that we cannot know whether social identification played a role in reducing the effects of secondary stressors and these effects disappeared in the months that followed. Nevertheless, social identification exerted main effects on the outcome variables in that it was positively associated with resilience and negatively associated with perceived stress (H4a). That is, a sense of belonging to some collective (e.g., one's family or community) was associated with reduced perceived stress and increased resilience. This finding is in line with the social cure approach in social psychology (see Haslam et al., 2012, 2018), which points to the beneficial effects of social connectedness on wellbeing.

Social support is particularly crucial during extreme events, the salutary effects of which have been empirically demonstrated in multiple studies (see Kaniasty & Norris, 1999; Norris et al., 2002). The post-disaster period is often characterised by a decline in the availability of social support (Kaniasty & Norris, 1999; Ntontis et al., 2020, 2022; Quarantelli, 1999). Similar was the case during the COVID-19 pandemic (Ntontis et al., 2022) with social support being abundant during the first few weeks and subsequently declining rapidly. Not receiving social support can reduce people's expectations of it, leading to potentially reduced psychological wellbeing (Kaniasty & Norris, 1999). Norris and Kaniasty (1996) suggest that such effects can be counteracted through the actual provision of social support, which can boost people's perceptions of its availability. Our analysis (H4b) showed that increased expectations of social support are associated with social identification (also see Ntontis et al., 2020). For our participants, experiencing higher levels of belonging to a group was associated with higher levels of expected social support and subsequently with reduced perceived stress and increased resilience. Thus, apart from the structural dimensions of feeling supported (i.e., by receiving support), a sense of social belonging through cohesive groups and communities is also crucial in boosting perceptions of support and thus boosting wellbeing.

In conclusion, we showed that secondary stressors were negatively associated with wellbeing. However, secondary stressors are tractable and amenable to reform, thus appropriate assessments can identify structural sources of stress and act in a timely manner to effectuate change. For example, it is possible for employers to make allowances for their employees, governments can financially support those in need, and healthcare systems can be boosted to alleviate concerns regarding access to timely healthcare. This paper's take-home message will probably apply to different types of crises and extreme events. Nevertheless, a contextualised approach is necessary since stressors will most likely differ across different contexts, cultures, and timepoints following an extreme event. On the other hand, systemic changes, the availability of social support, and investment in developing a sense of community can help ameliorate the negative effects of secondary stressors. If resilience is people's capacity to bounce back following a distressing event and is based on the availability of material and psychosocial resources that they have access to, then political motivation and initiatives to bring forward systemic reforms and facilitate access to resources for those most in need are paramount.

Limitations and recommendations for future research

Notwithstanding the theoretical and empirical contributions of our research, several limitations are worth noting. First, the cross-sectional nature of the data means we cannot ascertain the long-term effects of secondary stressors and/or their developmental trajectories. Ideally, future research should collect data that capture both the main impact as well as the long-term aftermath of an extreme event, as this will help identify trajectories of distress as a function of primary and secondary stressors and how their impacts might fluctuate over time.

Second, our outcome variables do not indicate psychopathology but rather people's reported distress which is common in extreme events. However, it is possible for enduring distress to develop into psychopathology under certain conditions (Norris et al., 2009). Thus, future research should conduct longitudinal surveys and incorporate clinical interviews when exploring relevant populations to explore whether persistent distress is associated with the development of psychopathology.

Third, we have not included measures of received social support. Receiving social support can boost social identity (Ntontis et al., 2020), leading in turn to further increases in expected social support (Häusser et al., 2022). Thus, future research should incorporate measures of received social support and assess both their psychosocial effects as well as the ways in which they can help reduce the impact of stressors over time.

Fourth, we did not control for the existence of possible previous traumatization that can also differ across genders and countries. For instance, those who have previously been exposed to war (or those from currently war-affected countries/regions) may be more affected by the global COVID-19 pandemic and the preventive measures that accompany it (Jeftić et al., 2021). Thus, future research should further explore the ways in which different crises (e.g., war and a pandemic) might intersect and harm people's ability to cope as well as the types of stressors they face. For this reason, bottom-up qualitative work is necessary that will conduct in-depth analysis in particular social contexts and will map the types of stressors present as well as their interrelationships.

While we attempted to collect data from many countries, not all were represented. Also, while conducting measurement alignment and filtering, responses collected from countries ($N < 30$) or language groups ($N < 100$) with small sample sizes were excluded due to methodological concerns. Therefore, this sample may not be representative of the global population and might be skewed towards people more inclined to participate in such surveys or with access to the tools and the opportunity to participate. Thus, an even more robust sampling strategy might be necessary in the future so that larger samples from more countries are collected.

References

Adler, N. E., Epel, E. S., Castellazzo, G. & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: preliminary data in healthy white women. *Health Psychology*. *19*, 586–592, https://doi.org/10.1037//0278-6133.19.6.586

Blackburn, A.M., Vestergren, S. & the COVIDiSTRESS II Consortium. (2022). COVIDiSTRESS diverse dataset on psychological and behavioural outcomes one year into the COVID-19 pandemic. *Scientific Data*, *9*, 331. https://doi.org/10.1038/s41597-022-01383-6

Chang, E. C. (1998). Dispositional optimism and primary and secondary appraisal of a stressor: Controlling for confounding influences and relations to coping and psychological and physical adjustment. *Journal of Personality and Social Psychology, 74*(4), 1109-1120. https://doi.org/10.1037/0022-3514.74.4.1109

Chen, F. F., & West, S. G. (2008). Measuring individualism and collectivism: The importance of considering differential components, reference groups, and measurement invariance. *Journal of Research in Personality, 42*(2), 259-294. https://doi.org/10.1016/j.jrp.2007.05.006

Cohen, S., Kamarck, T., Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, *24*(4), 385-396.https://doi.org/10.2307/2136404

Department of Health. (2009). *NHS emergency planning guidance: Planning for the psychosocial and mental health care of people affected by major incidents and disasters: Interim national strategic guidance*. Department of Health.

Drury, J., Brown, R., González, R., & Miranda, D. (2016). Emergent social identity and observing social support predict social support provided by survivors in a disaster: Solidarity in the 2010 Chile earthquake. *European Journal of Social Psychology*, *46*(2), 209–223. https://doi.org/10.1002/ejsp.2146

Drury, J., Carter, H., Cocking, C., Ntontis, E., & Tekin Guven, S. & Amlôt, R. (2019). Facilitating collective resilience in emergencies and disasters: Twelve recommendations based on the social identity approach. *Frontiers in Public Health*, *7*(141). https://doi.org/10.3389/fpubh.2019.00141

Fritz, C. (1965/1996). *Disasters and mental health: Therapeutic principles drawn from disaster studies. Historical and comparative disaster series #10*. University of Delaware: Disaster Research Center.

Goldmann, E., & Galea, S. (2014). Mental health consequences of disasters. *Annual review of public health*, *35*, 169-183. https://doi.org/10.1146/annurev-publhealth-032013-182435

Gómez-Salgado, J., Andrés-Villas, M., Domínguez-Salas, S., Díaz-Milanés, D., & Ruiz-Frutos, C. (2020). Related health factors of psychological distress during the COVID-19 pandemic in Spain. *International journal of environmental research and public health*, *17*(11), 3947. https://doi.org/10.3390/ijerph17113947

Goodman, E. et al. (2001). Adolescents' perceptions of social status: development and evaluation of a new indicator. *Pediatrics* 108, E31, https://doi.org/10.1542/peds.108.2.e31

Han, H. (2022). Testing the validity of the modified vaccine attitude question battery across 22 languages with a large-scale international survey dataset: within the context of COVID-19 vaccination. *Human Vaccines & Immunotherapeutics*, *18*(1), 2024066. https://doi.org/10.1080/21645515.2021.2024066

Han, H., Dawson, K. J., Walker, D. I., Nguyen, N., & Choi, Y. J. (2022). Exploring the association between character strengths and moral functioning. *Ethics & Behavior*. https://doi.org/10.1080/10508422.2022.2063867

Haslam, C., Jetten, J., Cruwys, T., Dingle, G. A., & Haslam, S. A. (2018). *The new psychology of health: Unlocking the social cure*. Routledge. https://doi.org/10.4324/9781315648569

Haslam, S. A., Reicher, S. D., & Levine, M. (2012). When other people are heaven, when other people are hell: How social identity determines the nature and impact of social support. In J. Jetten, C. Haslam, & S. A. Haslam (Eds.), *The social cure: Identity, health, and well-being* (pp. 157–174). Psychology Press.

Häusser, J., Abdel Hadi, S., Reichelt, C., & Mojzisch, A. (2022). The reciprocal relationship between social identification and social support over time: A four-wave longitudinal study. *British Journal of Social Psychology*, *62*(1). https://doi.org/10.1111/bjso.12553

Hobfall, S. E. (1988). *The Ecology of Stress.* Hemisphere.

Jeftić, A., Ikizer, G., Tuominen, J., Chrona, S., & Kumaga, R. (2021). Connection between the COVID-19 pandemic, war trauma reminders, perceived stress, loneliness, and PTSD in Bosnia and Herzegovina. *Current Psychology*. https://doi.org/10.1007/s12144-021-02407-x

Kaniasty, K., & Norris, F. H. (1995). In search of altruistic community: Patterns of social support mobilization following Hurricane Hugo. *American Journal of Community Psychology*, *23*(4), 447-477. https://doi.org/10.1007/BF02506964

Kaniasty, K., & Norris, F. (1999). The experience of disaster: individuals and communities sharing trauma. In R. Gist & B. Lubin (Eds.), *Response to disaster: Psychosocial, community, and ecological approaches* (pp. 25–62). Bruner/Mazel.

Kuldas, S., & Foody, M. (2022). Neither resiliency-trait nor resilience-state: Transactional Resiliency/e. *Youth & Society*, *54*(8), 1352-1376. https://doi.org/10.1177/0044118X211029309

Leys, C., Arnal, C., Wollast, R., Rolin, H., Kotsou, I., & Fossion, P. (2020). Perspectives on resilience: personality trait or skill?. *European journal of trauma & dissociation*, *4*(2), 100074. https://doi.org/10.1016/j.ejtd.2018.07.002

Lock, S., Rubin, G. J., Murray, V., Rogers, M. B., Amlôt, R., & Williams, R. (2012). Secondary stressors and extreme events and disasters: a systematic review of primary research from 2010-2011. *PLoS currents*, 4. https://doi.org/10.1371%2Fcurrents.dis.a9b76fed1b2dd5c5bfcfc13c87a2f24f

Lieberoth, A., Lin, S. Y., Stöckli, S., Han, H., Kowal, M., Gelpi, R., Flis, I., Sahin, H., Turk, F., Yeh, Y. Y., Ho, Y. W., Sikka, P., Delgado-Garcia, U., Lacko, D., Mamede, S., Zerhouni, O., Tuominen, J., Austin, T. B. & Dubrov, D. (2021). Stress and worry in the 2020 coronavirus pandemic: relationships to trust and compliance with preventive measures across 48 countries in the COVIDiSTRESS global survey. *Royal Society Open Science*, *8*(2), 200589. https://doi.org/10.1098/rsos.200589

Milfont, T. L., & Fischer, R. (2010). Testing measurement invariance across groups: Applications in cross-cultural research. *International Journal of Psychological Research*, *3*(1), 111-130. https://doi.org/10.21500/20112084.857

Mulchandani, R., Smith, M., Armstrong, B., English National Study of Flooding and Health Study Group, Beck, C. R., & Oliver, I. (2019). Effect of Insurance-Related factors on the association between flooding and mental health outcomes. *International journal of environmental research and public health*, *16*(7), 1174. https://doi.org/10.3390/ijerph16071174

Muthén, B., & Asparouhov, T. (2018). Recent methods for the study of measurement invariance with many groups: Alignment and random effects. *Sociological Methods & Research*, *47*(4), 637-664. https://doi.org/10.1177%2F0049124117701488

Norris, F. H., Friedman, M. J., Watson, P. J., Byrne, C. M., Diaz, E., & Kaniasty, K. (2002). 60,000 disaster victims speak: Part I. An empirical review of the empirical literature, 1981—2001. *Psychiatry*, *65*(3), 207-239. https://doi.org/10.1521/psyc.65.3.207.20173

Norris, F. H. & Kaniasty, K. (1996). Received and perceived social support in times of stress: A test of the social support deterioration deterrence model. *Journal of Personality and Social Psychology*, *71*(3), 498–511. https://doi.org/10.1037/0022-3514.71.3.498

Norris, F. H., Tracy, M., & Galea, S. (2009). Looking for resilience: Understanding the longitudinal trajectories of responses to stress. *Social science & medicine*, *68*(12), 2190-2198. https://doi.org/10.1016/j.socscimed.2009.03.043

Norris, F. H., & Uhl, G. A. (1993). Chronic stress as a mediator of acute stress: The case of Hurricane Hugo 1. *Journal of Applied Social Psychology*, *23*(16), 1263-1284. https://doi.org/10.1111/j.1559-1816.1993.tb01032.x

Ntontis, E., Drury, J., Amlôt, R., Rubin, G. J., &Williams, R. (2020). Endurance or decline of emergent groups following a flood disaster: Implications for community resilience. *International Journal of Disaster Risk Reduction*, *45*, 101493. https://doi.org/10.1016/j.ijdrr.2020.101493

Ntontis, E., Drury, J., Amlôt, R., Rubin, J. G., Williams, R., & Saavedra, P. (2021). Collective resilience in the disaster recovery period: Emergent social identity and observed social support are associated with collective efficacy, wellbeing, and the provision of social support. *British Journal of Social Psychology*, *60*, 1075 – 1095. https://doi.org/10.1111/bjso.12434

Ntontis, E., Fernandes-Jesus, M., Mao, G., Dines, T., Kane, J., Karakaya, J., Perach, R., Cocking, C., McTague, M., Schwarz, A., Semlyen, J., & Drury, J. (2022). Tracking the nature and trajectory of social support in Facebook mutual aid groups during the COVID-19 pandemic. *International Journal of Disaster Risk Reduction*, 103043. https://doi.org/10.1016/j.ijdrr.2022.103043

Pearlin, L. I. (1989). The sociological study of stress. *Journal of Health and Social Behavior,* 241-256. https://doi.org/10.2307/2136956

Picou, S. J., & Hudson, K. (2010). Hurricane Katrina and mental health: A research note on Mississippi Gulf Coast residents. *Sociological Inquiry*, *80*(3), 513-524. https://doi.org/10.1111/j.1475-682x.2010.00345.x

Postmes, T., Haslam, A., & Jans, L. (2013). A single-item measure of social identification: reliability, validity, and utility. *British Journal of Social Psychology, 52(4)*, 597-617.

Quarantelli, E. L. (1999). D*isaster related social behavior: Summary of 50 years of research findings.* Disaster Research Center. http://dspace.udel.edu/handle/19716/289

Sibley, C. G., Greaves, L. M., Satherley, N., Wilson, M. S., Overall, N. C., C. H. J., Milojev, P., Bulbulia, J., Osborne, D., Milfont, T. L., Houkamau, C. A., Duck, I. M., Vickers-Jones, R., & Barlow, F. K. (2020). Effects of the COVID-19 pandemic and nationwide lockdown on trust, attitudes toward government, and well-being. *American Psychologist*, *75*(5), 618–630. https://doi.org/10.1037/amp0000662

Smith, B. W., Dalen, J., Wiggins, K., Tooley, E., Christopher, P., & Bernard, J. (2008). The brief resilience scale: assessing the ability to bounce back. *International Journal of Behavioral Medicine*, *15*(3), 194-200. https://doi.org/10.1080/10705500802222972.

Stancombe, J., Williams, R., Drury, J., Collins, H., Lagan, L., Barrett, A., French, P. & Chitsabesan, P. (2022). People's experiences of distress and psychosocial care following a terrorist attack: interviews with survivors of the Manchester Arena bombing in 2017. *BJPsych open*, *8*(2). https://doi.org/10.1192/bjo.2022.2

Stokols, D. (1985). A congruence analysis of human stress. *Issues in Mental Health Nursing*, *7*(1-4), 35-64. https://doi.org/10.3109/01612848509009449

Tempest, E. L., English National Study on Flooding and Health Study Group, Carter, B., Beck, C. R., & Rubin, G. J. (2017). Secondary stressors are associated with probable psychological morbidity after flooding: a cross-sectional analysis. *The European Journal of Public Health*, *27*(6), 1042-1047. https://doi.org/10.1093/eurpub/ckx182

Vestergren, S. & COVIDiSTRESSII Collaboration (2021). COVIDiSTRESSII Global Survey. https://osf.io/36tsd/

Vignoles, V., Jaser, Z., Taylor, F., & Ntontis, E. (2021). Harnessing shared identities to mobilize resilient responses to the COVID-19 pandemic. *Political Psychology*, *42*(5), 817-826. https://doi.org/10.1111/pops.12726

Waite, T. D., Chaintarli, K., Beck, C. R., Bone, A., Amlôt, R., Kovats, S., Reacher, M., Armstrong, B., Leonardi, G., Rubin, G. J. & Oliver, I. (2017). The English national cohort study of flooding and health: cross-sectional analysis of mental health outcomes at year one. *BMC public health*, *17*(1), 1-9. https://doi.org/10.1186/s12889-016-4000-2

Westfall, J., & Yarkoni, T. (2016). Statistically controlling for confounding constructs is harder than you think. *PLOS One, 11*(3), e0152719. https://doi.org/10.1371/journal.pone.0152719

Williams, R., Kemp, V. J., Alexander, D. A. (2014). The psychosocial and mental health of people who are affected by conflict, catastrophes, terrorism, adversity and displacement. *In*: J. M. Ryan et al. (eds). *Conflict and Catastrophe Medicine*, (pp. 805–849). Springer. https://doi.org/10.1007/978-1-4471-2927-1_49

Williams, R., Ntontis, E., Alfadhli, K., Drury, J. & Amlôt, R. (2021). A social model of secondary stressors in relation to disasters, major incidents, and conflict: Implications for practice. *International Journal of Disaster Risk Reduction*, *63*. https://doi.org/10.1016/j.ijdrr.2021.102436

Supplementary Materials

Supplementary Methods

Measurement Invariance Testing

Our predictions concern cross-country comparisons, which require examination of measurement invariance; or testing whether participants from all countries complete the measures similarly (Chen & West, 2008; Milfont & Fischer, 2010). We examined this aspect across different language groups because participants were able to select the language that they did speak and then survey forms were presented in different languages as per their selection. First, for measures that employ latent variables (e.g., perceived stress [PSS]), we conducted a multigroup confirmatory factor analysis (MGCFA) to examine measurement invariance. If scalar invariance (equal loadings and intercepts) is achieved, then we would use composite scores for further analyses. In this process, a robust estimator, weighted least square mean and variance adjusted (WLSMV) estimator, instead of a default maximum likelihood estimator, as the scales employed ordinal scales (Li, 2016). For this test, we started with examining configural invariance, which assumes an equal measurement model across all 15,130 samples in 28 languages without any further constraints. We concluded that configural invariance was achieved if the model fit was acceptable in terms of the root mean square error of approximation (RMSEA) and standardized root mean squared residual (SRMR) $< .08$ and comparative fit index (CFI) $\geq .90$ (Chen & West, 2008). Once configural alignment was achieved, we examined metric invariance, which assumes equal factor loadings across groups. Metric invariance was tested in terms of changes in the fit indicators, i.e., ΔRMSEA $< +.015$, ΔSRMR $< + .30$, ΔCFI $\geq -.01$ (Putnick & Bornstein, 2016). If metric invariance was achieved, we then tested scalar invariance, which assumes the equal loadings and intercepts across groups. In the same vein, the achievement of scalar invariance was examined with changes in the fit indicators, e.g., ΔRMSEA $<$ $+.015$, ΔSRMR $< + .015$, ΔCFI $\geq -.01$ (Putnick & Bornstein, 2016).

If measurement invariance was not achieved, then measurement alignment would be conducted with *sirt* to address the non-invariance. With the package, factor loadings and intercepts are adjusted to absolve existing non-invariance. Once the loadings and intercepts are adjusted through the process, we calculated the latent factor scores to be used in further analyses. Whether measurement alignment was conducted successfully was evaluated with $R^2_{loading}$ and $R^2_{intercepts}$ that indicate the extent to which the measurement non-invariance existing in factor loadings and intercepts, respectively, were successfully absorbed. We assumed that alignment was successful and confirmed scalar invariance when both values were .75 or higher (Muthén & Asparouhov, 2018).

For additional information regarding whether measurement alignment is performed properly, we conducted a repeated simulation based on Monte Carlo simulation proposed in Muthén and Asparouhov (2018). This simulation-based validation is similar to what was conducted by Lieberoth et al. (2021; see supplementary materials for technical further details), but with R in the present article. We generated a simulation dataset with factor loadings and intercepts in the original dataset in different sample sizes, n = 100, 200, and 500 per group. Measurement alignment is performed with the generated dataset. In addition, MGCFA was also performed with the same generated simulation dataset for cross-validation. We then examined the correlation between factor means from measurement alignment and those from confirmatory factor analysis (CFA). For additional information, we also calculated the correlation of factor variances. $R^2_{loading}$ and $R^2_{intercepts}$ were also estimated. This procedure was repeated 500 times for each sample size. In this process, to improve computational power for the repetitive cross-validation process, we utilized multi-processing by modifying the codes composed by Han et al. (2022). To evaluate whether measurement alignment is consistently and reliably conducted, we examined whether the mean correlation coefficient of factor means ≥ .95.

Models for All Hypotheses

For H1, we computed a regression with stress and resilience as response variables and primary stressors as a predictor.

For H2, we computed a regression with stress and resilience as response variables and secondary stressors as a predictor. For H3a, we computed regressions with different demographics and their interaction terms with secondary stressors. For example, we computed a regression with gender and its interaction with secondary stressors, a regression with employment and its interaction with secondary stressors, or a regression with education and its interaction with secondary stressors. For H3b, we compute an additional regression with social identification and its interaction with secondary stressors. For these analyses involving interaction effects, we compared the candidate model with interaction effects and the model only with main effects with model Bayes Factors (BFs). If a model BF indicating to what extent the model with interaction effects better was supported by evidence compared with the model only with main effects was higher than the aforementioned threshold, BF = 3, then we assumed that the interaction effects significantly improved the prediction model. Otherwise, we concluded that the model only with main effects was superior to the model with interaction effects, so the interaction effects shall not be considered significant.

For H4a and H4b, we computed a mediation analysis with social identification (mean score) as predictor, expected support as mediator, and stress and resilience as response variables. For testing these hypotheses, we employed Bayesian multilevel modeling (MLM) with *brms* to be able to include random slopes in the mediation model. We computed the same model with a frequentist approach (mediation package). Frequentist mediation analysis was not conducted since it was not suitable for testing a random effect model with random slopes.

Model Selection and Multilevel Modeling

We computed descriptive statistics and conducted frequentist and Bayesian multilevel modelling. We computed mixed-effects regression analyses for our hypotheses with R packages (e.g., brms, lme4, lmerTest and mediation). First, to identify the best model (see Table S8), we conducted Bayesian multilevel modelling (MLM) with the Gaussian family and the default Cauchy prior, Cauchy ($x_0 = 0$, $\gamma = 1$) with *brms* (Rouder & Morey, 2012). We specified a random structure for countries by entering a random intercept and slope. To identify the best model during the process, we examined which model demonstrates the greatest Bayes Factor (BF) indicating to what extent a specific model is more favourable supported by evidence than alternative models with brms. For instance, when Models A and B are compared and the resultant BF is 10, it means that Model A is ten times more strongly supported by data compared with Model B (Wagenmakers et al., 2018).

We calculated model BFs for best model exploration. M1 (model with fixed effects and random intercepts) and M2 (model with fixed effects, random slopes, and intercepts) were compared with the null model, M0 (model only with random effects). Then, model BFs, BF_{10} and BF_{20}, which indicate to what extent M1 and M2, respectively, were better supported by evidence compared with M0. In the same way, we also calculated BF_{21} to examine whether M1 or M2 best predicted an outcome variable of interest. When a model BF value was extremely high (e.g., $BF >> 100$), we reported log(BF) instead of BF for brevity. In this process, continuous variables were mean-centered. Once the best model was identified, we examined whether the predictor(s) interest were significant. We assumed that the predictor(s) of interest demonstrating $BF \geq 3$ indicated presence of positive evidence supporting a hypothesis of interest. In addition, for a sensitivity test, we conducted the same Bayesian MLM with a non-informative normal distribution prior, N (0, 10^6), for all fixed effects as per *brms* suggestion. We examined whether the hypothesis testing results in terms of BFs were significantly altered when the normal distribution prior was employed.

Then, we conducted frequentist MLM with the identified best model. We used 95% confidence intervals and the conventional 5% significance level ($p < .05$) for null hypothesis significance testing. Effect size indicators in terms of Cohen's *d* were calculated for the predictor(s) of interest for additional information. We obtained marginal and conditional R^2s and reported estimates for all fixed effects of the mixed-effects regression models. We also computed intraclass correlation coefficients (ICCs) to examine the sizes of the random effects across countries. Although we did not evaluate the calculated ICCs with a specific cutoff value, we considered ICC ≥ .25 as the presence of substantial random effects (Guo, 2005). If ICC ≥ .25 was not achieved, then we compared the best model and the best model minus random effect(s) in terms of model BFs to examine whether the inclusion of random effect(s) was justifiable.

We produced diagnostic plots to verify assumptions of normality (i.e., to test whether the model has normally-distributed residuals). If these assumptions are violated, we applied a suitable transformation (e.g., log, inverse). We computed variance inflation factors (VIFs) to check for multicollinearity. When VIF exceeded 3.0, which indicates that 67% of the variance in one predictor can be explained by the other predictors, we assumed that there would be substantial multicollinearity between predictors (Thompson et al., 2017). Where we could not solve non-convergence or singular fit problems, we removed the random structure.

Initially, we planned to compute common frequentist model fit indices for our mediation models (e.g., CFI, RMSEA). However, as we employed Bayesian mediation analysis with *brms* to include random effects in our models, we examined model BFs as model performance indicators in lieu of the aforementioned frequentist indices. In the Supplementary Materials, we specify the models for all hypotheses. Please note that we refer to the variable names defined in the survey / material preregistration (see https://osf.io/36tsd/). Furthermore, note that we added covariates to all models specified below (for robustness check reasons; see https://osf.io/36tsd/ for a list of covariates).

Supplementary Results

Using structural equation modelling to address potential false positives in predicting stress and resilience with secondary stressors, social identification, and expected support.

When we examined whether social identification and expected support significantly predicted stress and resilience along with secondary stressors, the results indicated the significant effects of both additional predictors. However, Westfall and Yarkoni (2016) pointed out an issue related to potentially inflated false positives in such a case. They argued that simply testing the incremental validity of additional predictors via conventional regression analysis is likely to produce spurious conclusions even if the associations are found to be significant. To address this issue, following Westfall and Yarkoni's (2016) suggestion, we conducted structural equation modelling (SEM), which allowed us to address possible measurement errors. Due to the complexity of the analysis process, simple SEM that does not consider random effects was performed.

Figures S7 and S8 show the results from SEM when perceived stress and resilience were predicted by secondary stressors, social identification, and expected support, respectively. In both cases, acceptable model fit was supported. For prediction of perceived stress, RMSEA = .077, SRMR = .074, CFI = .919. When resilience was predicted, RMSEA = .042, SRMR = .039, CFI = .979. In all cases, the pathways between all predictors and dependent variables were significant, $p < .001$. The results suggest that the incremental validity of social identification and expected support within the context of predicting stress and resilience with secondary stressors can be supported by SEM, which is more robust against measurement errors and inflated false positives than conventional regression analysis.

Additional exploratory analyses: Secondary stressors as mediating the relationship between demographic characteristics and stress and resilience.

Secondary stressors as mediating the relationship between demographic characteristics and perceived stress

First, we examined whether the relationship between gender, SES, and PSS was significantly mediated by secondary stressors. Similar to testing H4a and H4b, we started with comparing the null, random intercept, and random slope models. When the three models were compared, the model BF of the random slope model was highest although it was not decisively superior to the random intercept model (see Table S9).

When gender in the random slope model was examined, we found that the relationship between gender and perceived stress was significantly but partially mediated by secondary stressors (see Table S10). All hypothesized paths were also found to be significantly non-zero (see Table S11). The same trend was found when SES was examined since the relationship between gender and perceived stress was partially mediated by secondary stressors (see Table S10). All hypothesized pathways were also significantly non-zero (see Table S11).

Secondary stressors as mediating the relationship between demographic characteristics and resilience

Second, we tested whether the association between gender, SES, and resilience was mediated by secondary stressors. When the three models were compared, the random slope model was found to be the best one given the model BFs although the BF between the random intercept and slope models was not decisive (see Table S9).

We started with examining gender as a predictor. In this case, we found that the relationship between gender and resilience was partially mediated by secondary stressors (see Table S10). All tested pathways were found to be significantly non-zero (see Table S11). The similar trend was reported when SES was examined as a predictor; the relationship between SES and resilience was also partially mediated by secondary stressors (see Table S10). Similarly, all tested paths were significantly non-zero (see Table S11).

Both mediation analyses reported above highlight that men and people of higher SES experience lower stress and higher resilience compared to women and people of lower SES, partially due to experiencing lower levels of secondary stressors.

Supplementary Tables and Figures

Table S1

Descriptive statistics by country (43 countries)

		Primary stressor		Secondary stressor		Expected Support Scale		Social identification		Expected Stress Scale		Brief Resilience Scale	
	N	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
All countries	14,600	1.87	1.00	1.54	1.07	5.05	1.44	2.11	.43	4.33	1.24	3.43	1.45
1. Belarus	34	2.02	.86	2.01	1.13	5.25	1.06	2.16	.32	4.35	1.03	3.65	1.32
2. Bolivia	114	2.60	.84	2.00	.96	4.70	1.48	2.24	.33	4.60	1.13	3.65	1.53
3. Bosnia and Herzegovina	108	1.78	1.08	1.61	1.04	5.23	1.43	2.22	.31	4.59	.95	3.51	1.25
4. Brazil	448	2.41	.87	1.59	1.13	5.35	1.34	2.28	.43	4.17	1.24	3.62	1.14
5. Bulgaria	299	1.43	1.07	1.37	1.06	4.96	1.56	2.17	.43	4.65	1.29	3.66	1.31
6. Colombia	548	2.08	.97	1.84	1.10	5.08	1.48	2.19	.36	4.51	1.33	3.48	1.32
7. Costa Rica	270	2.20	.87	1.84	1.09	5.43	1.29	2.19	.37	4.58	1.26	3.70	1.39
8. Czech Republic	365	1.49	.94	1.44	1.06	5.32	1.33	2.19	.37	4.12	1.23	3.28	1.24
9. Denmark	127	1.29	.92	.70	.80	5.41	1.16	2.13	.30	4.85	1.18	4.12	1.19
10. Ecuador	291	2.24	.91	2.11	1.06	5.13	1.44	2.18	.37	4.47	1.06	3.59	1.55
11. Estonia	246	1.41	.93	1.13	.97	5.01	1.40	2.06	.39	4.34	1.13	2.95	1.28
12. Finland	962	1.45	.93	.85	.85	5.24	1.50	1.94	.38	4.65	1.37	3.80	1.35
13. Germany	146	1.84	.89	1.26	.93	5.16	1.36	2.18	.32	4.43	1.26	3.49	1.14
14. Guatemala	287	2.07	.94	1.74	.94	5.53	1.23	2.28	.32	4.66	1.14	3.82	1.30
15. Honduras	429	2.03	.88	2.17	.99	4.71	1.38	2.17	.38	4.38	1.06	2.77	1.74

16. Hong Kong	40	1.62	.84	1.38	1.05	5.51	1.20	2.10	.30	4.13	1.16	3.53	1.27
17. Ireland	397	2.21	.90	1.52	1.05	5.11	1.43	2.30	.36	4.38	1.33	4.18	1.17
18. Italy	309	1.82	1.02	1.71	1.01	4.80	1.48	2.14	.34	4.33	1.37	3.30	1.28
19. Japan	2,132	1.86	1.03	1.67	1.05	3.96	1.37	1.66	.44	3.76	1.22	2.57	1.43
20. Kazakhstan	36	1.71	.90	1.88	.94	5.44	1.34	2.24	.28	4.58	.92	3.76	1.24
21. Kyrgyzstan	254	1.88	.98	1.86	.95	5.14	1.22	2.23	.33	4.44	1.08	3.59	1.49
22. Lebanon	141	2.27	1.01	2.01	.94	5.03	1.36	2.39	.36	4.53	1.08	4.58	1.24
23. Malaysia	223	2.78	.88	2.28	1.20	4.86	1.36	2.29	.44	4.19	1.18	3.64	1.40
24. Maldives	39	2.66	.88	1.97	1.22	4.91	1.63	2.32	.36	4.17	1.30	3.91	1.27
25. Nepal	37	2.56	.97	2.13	1.38	5.03	1.40	2.36	.32	3.98	1.12	3.22	1.64
26. New Zealand	38	1.40	.95	1.01	.92	5.70	1.10	2.07	.37	4.84	1.36	3.95	1.12
27. Norway	373	1.79	.94	.99	.89	5.29	1.44	2.16	.36	4.72	1.29	4.15	1.24
28. Other	30	1.57	1.16	1.86	.89	5.13	1.63	2.05	.49	4.52	.82	3.51	1.55
29. Pakistan	151	2.01	1.15	1.81	1.07	4.92	1.35	2.30	.47	4.12	.91	3.62	1.56
30. Portugal	484	2.17	.89	1.42	1.04	5.35	1.25	2.21	.39	4.28	1.21	3.75	1.25
31. Russia	2,259	1.61	.95	1.74	1.04	5.33	1.30	2.25	.38	4.41	1.05	3.44	1.60
32. Slovakia	313	1.91	.82	2.06	.93	5.16	1.36	2.23	.31	3.94	1.27	2.93	1.19
33. South Africa	44	2.55	.84	1.41	1.13	5.47	1.10	2.32	.38	4.65	1.12	3.87	1.25
34. Spain	574	2.03	.86	1.62	.99	5.50	1.33	2.17	.39	4.47	1.28	3.48	1.29
35. Sweden	132	1.44	.86	.79	.82	5.35	1.35	2.20	.35	4.37	1.24	4.04	1.24
36. Switzerland	589	1.58	.91	.88	.86	5.58	1.11	2.07	.31	4.89	1.11	3.73	1.16
37. Taiwan	221	1.82	.86	1.50	.85	5.15	1.19	1.98	.30	4.50	1.10	3.52	1.17
38. Turkey	199	2.09	.97	2.40	.97	4.76	1.53	2.30	.33	4.18	1.29	3.23	1.06

39. Uganda	135	2.92	.93	2.34	1.17	4.78	1.29	2.29	.42	4.26	.86	3.95	1.38
40. Ukraine	252	1.48	.94	1.13	.84	5.27	1.43	2.27	.35	3.95	1.21	3.54	1.34
41. United Kingdom	125	2.23	.95	1.49	.87	5.30	1.43	2.21	.36	4.45	1.32	3.93	1.14
42. United States	111	2.12	1.07	1.61	1.07	5.10	1.58	2.18	.39	4.41	1.40	3.59	1.34
43. Uruguay	288	1.96	.86	1.32	.98	5.80	1.14	2.13	.30	4.62	1.17	3.77	1.28

Table S2

Results of measurement invariance test

Scale	RMSEA	SRMR	CFI	ΔRMSEA	ΔSRMR	ΔCFI
Primary stressors						
Configural invariance						
	.329	.099	.701			
Secondary stressors						
Configural invariance						
	.104	.031	.968			
Perceived Support Scale						
Configural invariance						
	.000	.000	1.000			
Metric invariance						
	.055	.020	.989	+.055	+.020	-.011
Social identification						
Configural invariance						
	.102	.031	.965			
PSS						
Configural invariance						
	.095	.063	.874			

BRS			
Configural invariance			
	.093	.037	.953

Table S3

Results of measurement alignment

Scale	$R^2_{loadings}$	$R^2_{intercepts}$
Primary stressors	.96	.99
Secondary stressors	.97	.98
Expected Support	.99	1.00
Social identification	.95	.99
PSS	.99	.99
BRS	.98	1.00

Note. The repeated Monte Carlo simulation test also confirmed that the alignment process was completed in a reliable and consistent manner in all scales given the reported mean correlation of factor means was higher than .95. This indicates a high level of confidence in the factor means obtained from the alignment method for all scales across the 24 languages in our sample. Table S4 provides the results from the repeated simulation test.

Table S4

Results of repeated simulation test for measurement alignment across 500 repetitions

Scales	Indicators	*n* = 100		*n* = 200		*n* = 500	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Primary stressors	*cor* (mean)	.96	.02	.97	.01	.97	.01
	cor (var)	.60	.16	.67	.12	.70	.08
	$R^2_{loadings}$	.77	.41	.91	.13	.94	.01
	$R^2_{intercepts}$	.95	.13	.96	.03	.96	.01
Secondary stressors	*cor* (mean)	.95	.02	.95	.02	.95	.02
	cor (var)	.31	.14	.38	.13	.43	.11
	$R^2_{loadings}$	.95	.03	.96	.01	.97	.00
	$R^2_{intercepts}$	.96	.01	.97	.01	.96	.01
Perceived Support Scale	*cor* (mean)	.99	.01	.99	.01	.99	.00
	cor (var)	.95	.03	.95	.02	.95	.02
	$R^2_{loadings}$	.99	.00	.99	.00	.99	.00
	$R^2_{intercepts}$	1.00	.00	1.00	.00	1.00	.00
Social identification	*cor* (mean)	.96	.01	.97	.01	.97	.01
	cor (var)	.87	.05	.87	.04	.87	.03
	$R^2_{loadings}$	.96	.00	.96	.00	.96	.00
	$R^2_{intercepts}$	.97	.00	.97	.00	.97	.00
PSS	*cor* (mean)	.96	.05	.97	.04	.98	.01
	cor (var)	.86	.07	.89	.06	.94	.03
	$R^2_{loadings}$	.91	.06	.94	.04	.97	.01

	$R^2_{intercepts}$	.97	.05	.98	.04	.99	.00
BRS	*cor* (mean)	.99	.00	.99	.00	.99	.00
	cor (var)	.89	.04	.89	.03	.89	.03
	$R^2_{loadings}$	.98	.01	.98	.00	.98	.00
	$R^2_{intercepts}$	1.00	.00	1.00	.00	1.00	.00

Note. *cor* (mean): correlation between the factor means estimated with MGCFA and those estimated with measurement alignment. *cor* (var): correlation between the factor variances estimated with MGCFA and those estimated with measurement alignment.

Table S5

Model comparisons and Intraclass correlation (ICC)

	H1		H2		H4b	
	Stress	Resilience	Stress	Resilience	Stress	Resilience
M1 vs. M0 (logBF)	Infinite	602.84	Infinite	Infinite	15,534.42	12,910.07
M2 vs. M0 (logBF)	Infinite	603.54	Infinite	Infinite	15,543.41	12,910.84
M2 vs. M1 (logBF)	11.35	1.86	18.28	-2.90	8.99	1.92
Best model	M2	M2	M2	M1	M2	M2
Best model adjusted ICC	.07	.05	.06	.04	N/A	N/A
Best model conditional ICC	.05	.05	.05	.04	N/A	N/A
Best model without random effects vs. M0 (logBF)	638.30	378.83	1,959.67	1,382.49	14,883.20	12,668.14
Best model without random effects vs. M1 (logBF)	-262.76	-224.10	-199.24	-167.22	-659.93	-243.93
Best model without random effects vs. M2 (logBF)	-274.15	-224.58	-217.41	-164.47	-651.18	-241.68

Note. ICCs could not be calculated for H4b because the functionality was not available for mediation models.

Table S6

Results of the significance tests of the model paths in the "global" model

	b	*SE*	BF (one-tailed)	95% Bayesian CI Lower	95% Bayesian CI Upper
DV = perceived stress					
Primary stressors	.14	.02	Infinite	.11	.17
Secondary stressors	.26	.01	Infinite	.24	.29
Social identification	-.03	.01	221.22	-.06	-.01
Expected support	-.26	.02	Infinite	-.28	-.23
Secondary stressors x social identification	-.01	.01	.01	-.03	.01
Primary stressors x expected support	.01	.01	.02	-.01	.03
Secondary stressors x expected support	.01	.01	.01	-.01	.03
Social identification → expected support	.21	.01	Infinite	.29	.24
DV = resilience					
Primary stressors	-.09	.01	Infinite	-.11	-.07
Secondary stressors	-.15	.01	Infinite	-.17	-.13
Social identification	.08	.01	Infinite	.06	.10

Expected support	.24	.01	Infinite	.22	.26
Secondary stressors x Social identification	.02	.01	.02	-.01	.04
Primary stressors x expected support	-.02	.01	.02	-.04	.01
Secondary stressors x expected support	-.03	.01	.21	-.05	-.01
Social identification → expected support	.22	.01	Infinite	.22	.26

Notes. The best model for DV = perceived stress was M_2, log(BF[M2vsM0]) = 5,144.85, log(BF[M2vsM1]) = 10.43, log(BF[M2vsFixedOnly]) = 486.68. The best model for DV = resilience was M1, log(BF[M1vsM0]) = 4,009.52, log(BF[M1vsM2]) = 12.21, log(BF[M1vsFixedOnly]) = 220.50.

Table S7

Exploratory mediation analysis results of the "global" model (social identification → expected support → stress/resilience)

	DV = perceived stress			DV = resilience		
		95% CI			95% CI	
	Estimated	Lower	Upper	Estimated	Lower	Upper
Direct effect (ADE)	-.03	-.06	-.01	.09	.06	.12
Indirect effect (ACME)	-.05	-.07	-.04	.05	.04	.06
Mediator effect	-.26	-.29	-.21	.22	.18	.26
Total effect	-.09	-.12	-.06	.14	.10	.17
% mediated	60.87%	40.13%	81.61%	35.30%	24.66%	45.95%

Table S8

Description of models tested

Model	**Model Specification**
Null model (M0)	Stress/Resilience~ control variables + (1|country)
Random intercept model (M1)	Stress/Resilience~ predictor(s) + control variables + (1|country)
Random slope model (M2)	Stress/Resilience~ predictor(s) + control variables + (1 + predictor(s)|country)

Table S9

Model comparisons for the exploratory mediation analysis (demographics → secondary stressors → Stress/Resilience)

log Model BF	Perceived stress	Resilience
M1 vs. M0	1,961.46	1,192.11
M2 vs. M0	1,961.48	1,192.15
M2 vs. M1	.02	.04
Examined Best model	M2	M2

Table S10

Exploratory mediation analysis results (demographics → secondary stressors → stress/resilience)

	DV = perceived stress			DV = resilience		
	Treatment = gender (man)			Treatment = gender (man)		
		95% CI			95% CI	
	Estimated	Lower	Upper	Estimated	Lower	Upper
Direct effect (ADE)	-.20	-.23	-.16	-.10	-.11	-.09
Indirect effect (ACME)	-.05	-.06	-.03	-.06	-.07	-.06
Mediator effect	.36	.34	.37	.36	.34	.37
Total effect	-.24	-.28	-.20	-.16	-.18	-.15
% mediated	19.34%	13.25%	25.43%	37.94%	34.23%	41.65%
	Treatment = SES			Treatment =SES		
		95% CI			95% CI	
	Estimated	Lower	Upper	Estimated	Lower	Upper
Direct effect (ADE)	.20	.15	.25	.10	.08	.11
Indirect effect (ACME)	.03	.02	.04	.04	.03	.04
Mediator effect	-.23	-.25	-.20	-.23	-.25	-.20
Total effect	.23	.18	.28	.14	.12	.15

% mediated	13.20%	8.04%	18.36%	28.27%	23.98%	32.57%

Table S11

Results of the significance tests of the model paths (demographics → secondary stressors → stress/resilience)

	b	*SE*	BF (one-tailed)	95% Bayesian CI Lower	95% Bayesian CI Upper
DV = perceived stress					
Gender	-.20	.02	Infinite	-.23	-.16
SES	-.10	.01	Infinite	-.11	-.09
Secondary stressors	.35	.01	Infinite	.34	.37
Gender → Secondary stressors	-.13	.02	Infinite	-.17	-.10
SES → Secondary stressors	-.17	.01	Infinite	-.18	-.16
DV = resilience					
Gender	.20	.02	Infinite	.16	.24
SES	.10	.01	Infinite	.09	.11
Secondary stressors	-.23	.01	Infinite	-.25	-.21
Gender → Secondary stressors	-.14	.02	Infinite	-.17	-.10

SES						
→ Secondary stressors	-.17		.01	Infinite	-.18	-.16

Figure S1

Linearity assumption check results for the association between primary stressors and PSS.

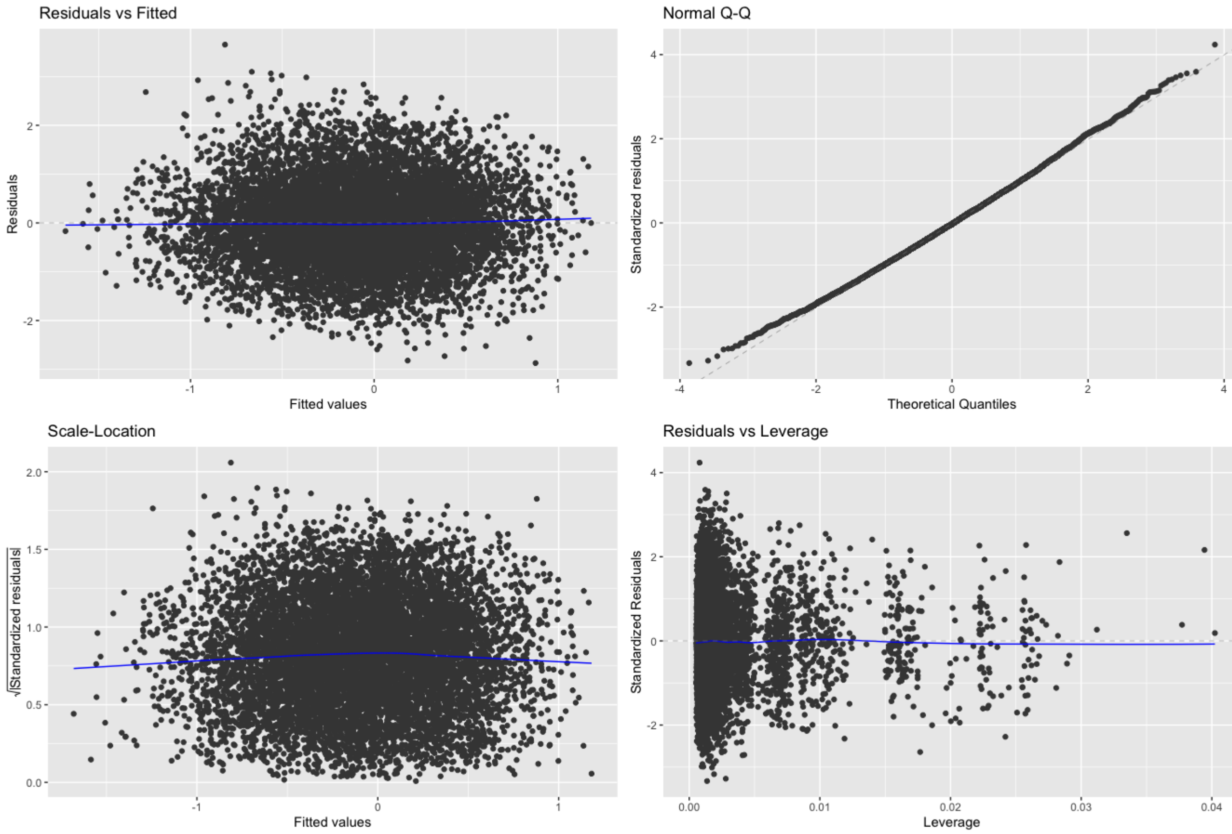


Figure S2

Linearity assumption check results for the association between primary stressors and BRS.

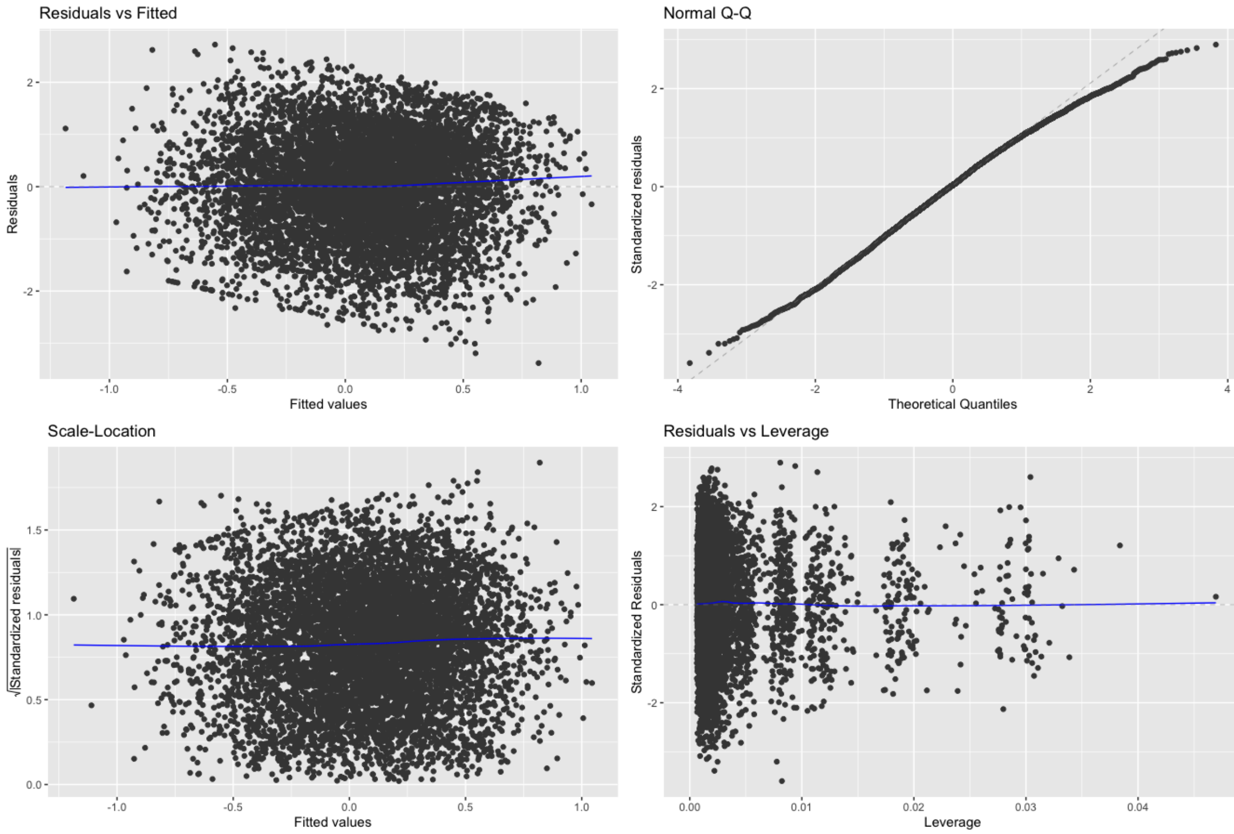


Figure S3

Linearity assumption check results for the association between secondary stressors, social identification, and PSS.

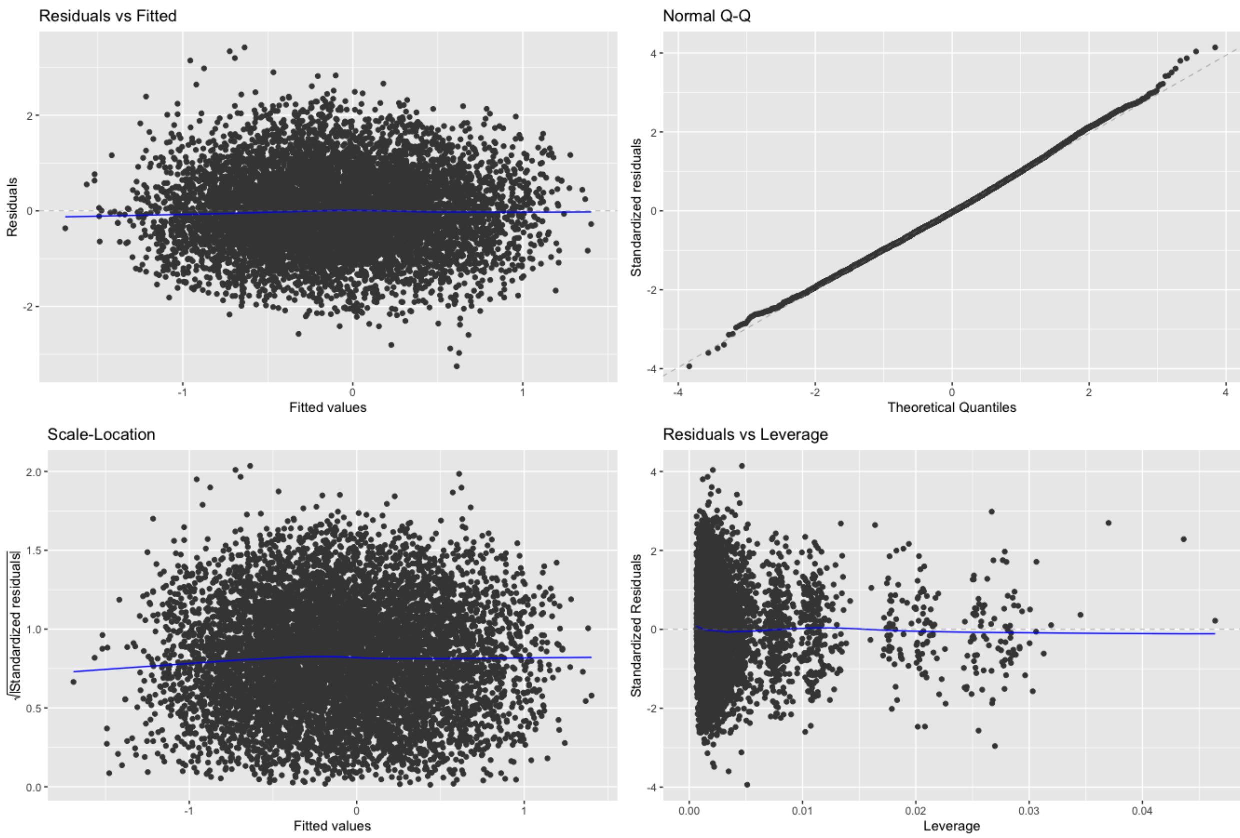


Figure S4

Linearity assumption check results for the association between secondary stressors, social identification, and BRS.

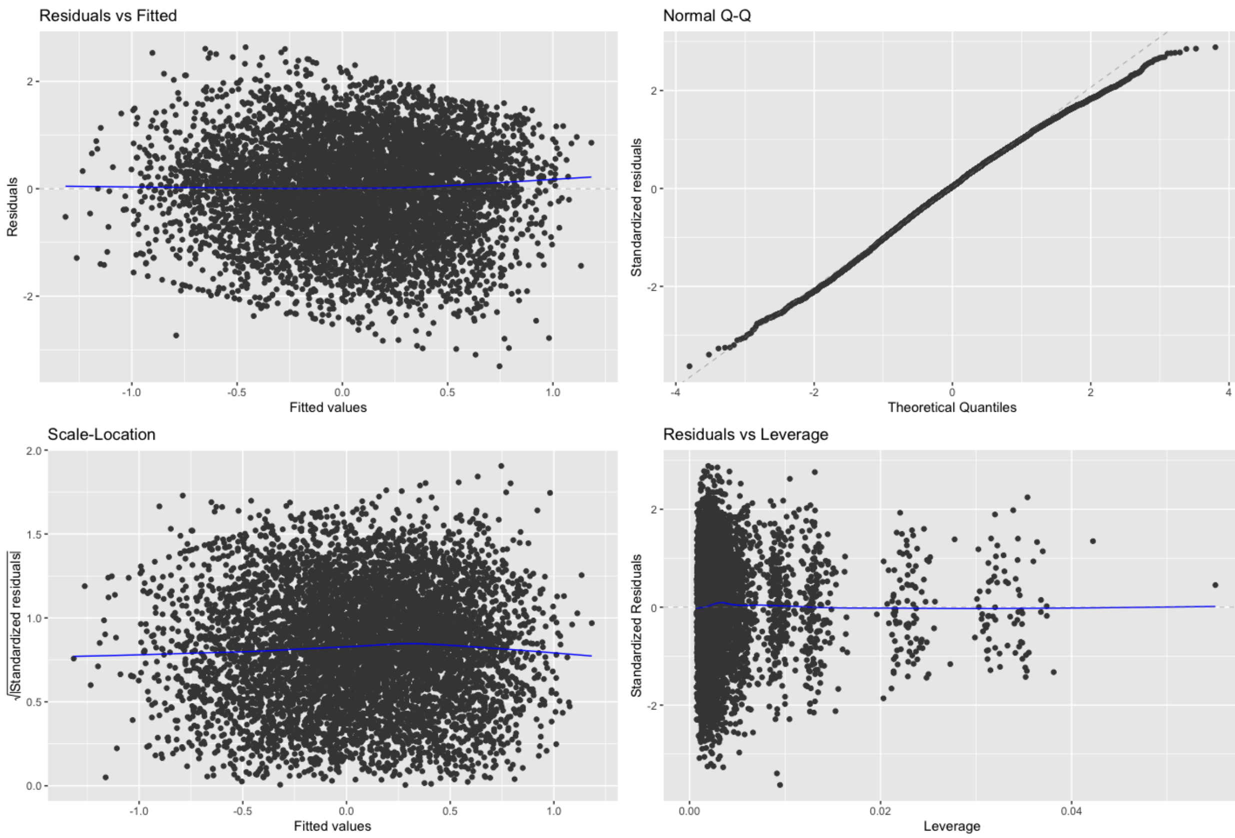


Figure S5

Linearity assumption check results for the association between social identification, Expected Support Scale, and PSS.

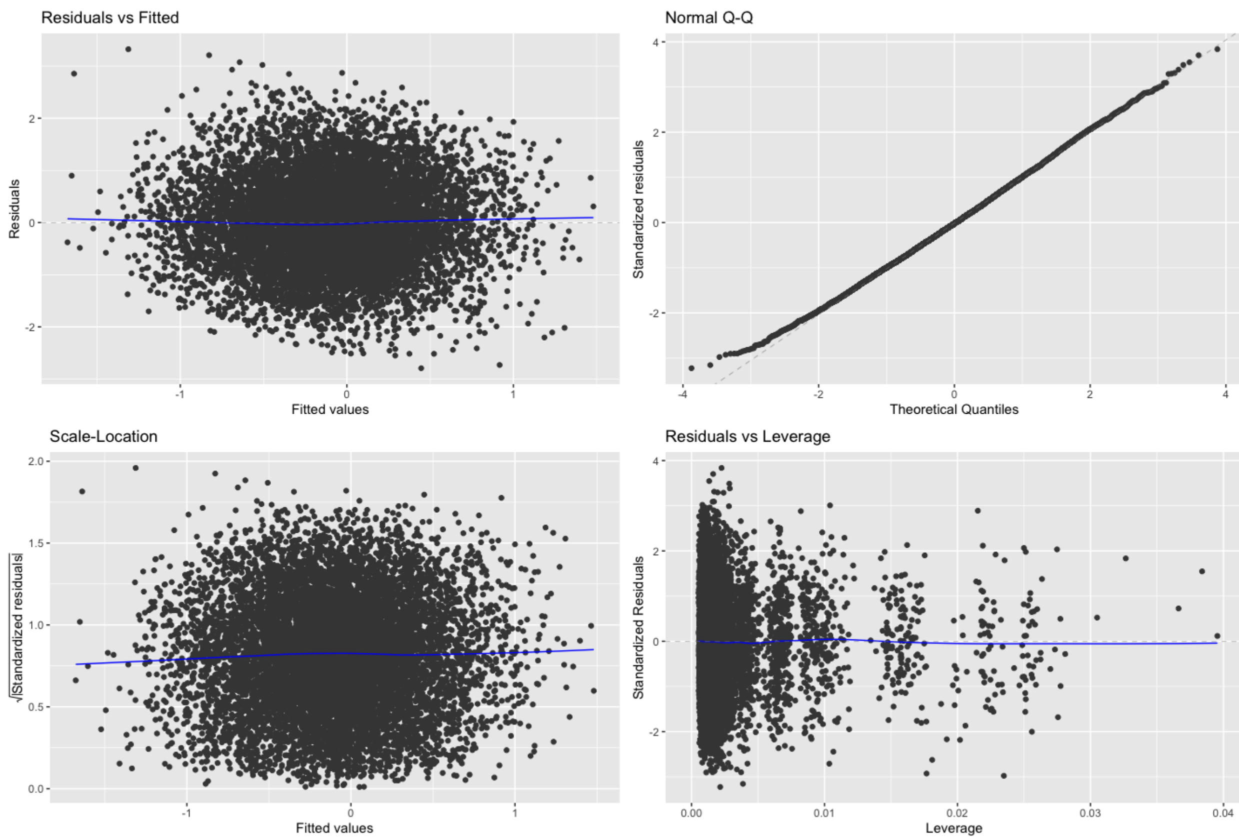


Figure S6

Linearity assumption check results for the association between social identification, Perceived Support Scale, and BRS.

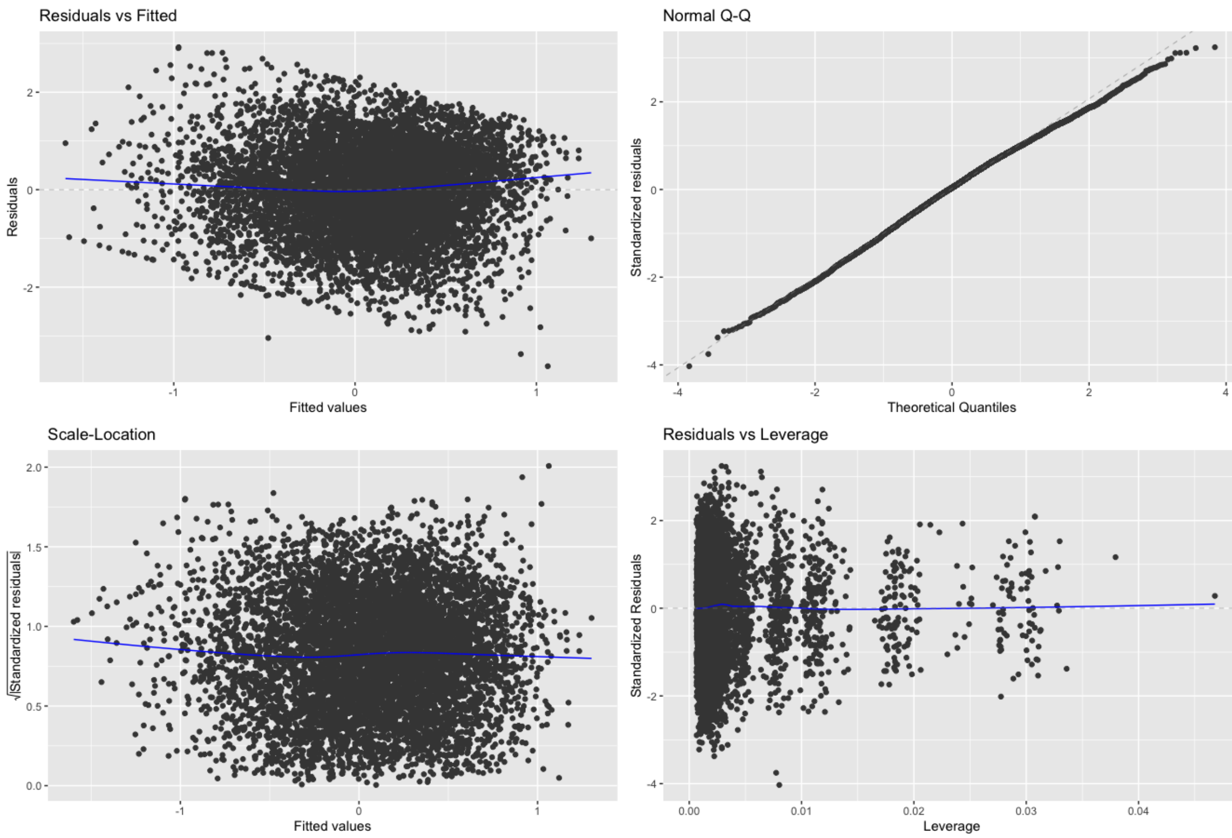


Figure S7

Path diagram for a SEM predicting perceived stress, allowing for specified degrees of reliability in secondary stressors (SS), social identification (GID), and expected social support (SPS).

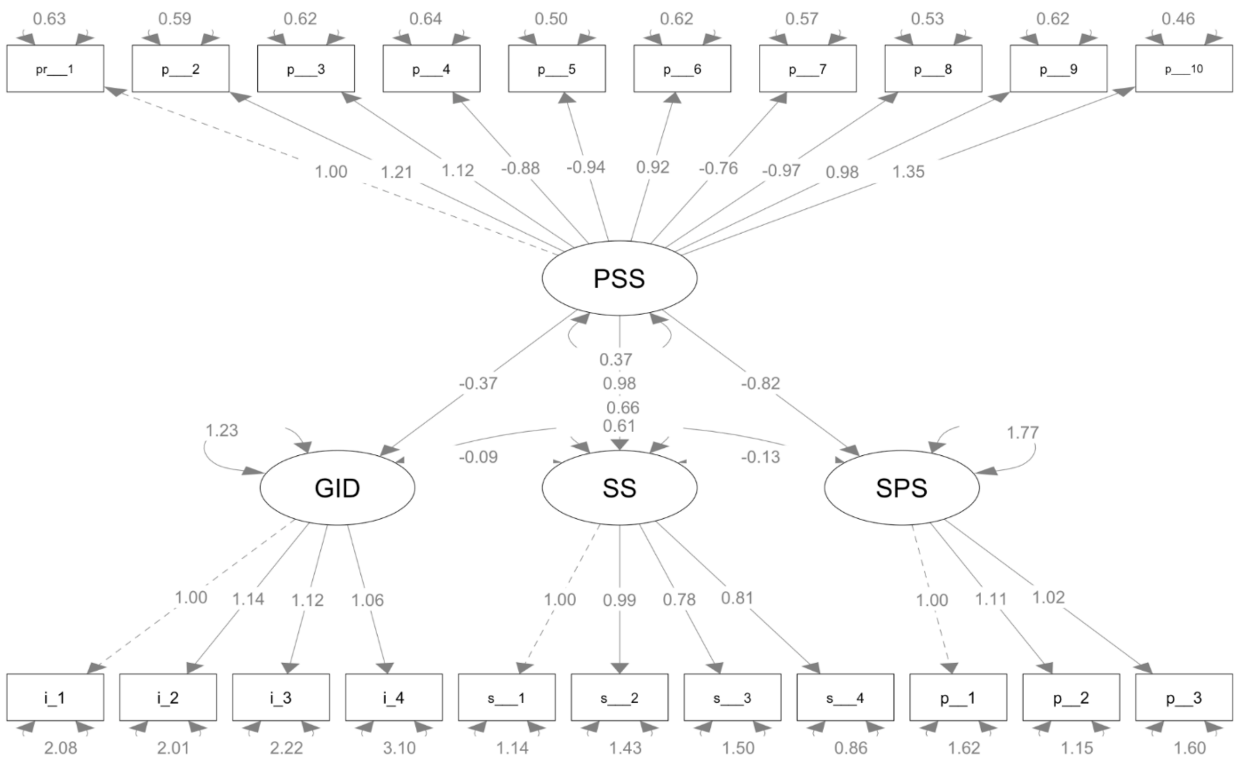


Figure S8

Path diagram for a SEM predicting resilience, allowing for specified degrees of reliability in secondary stressors (SS), social identification (GID), and expected social support (SPS).

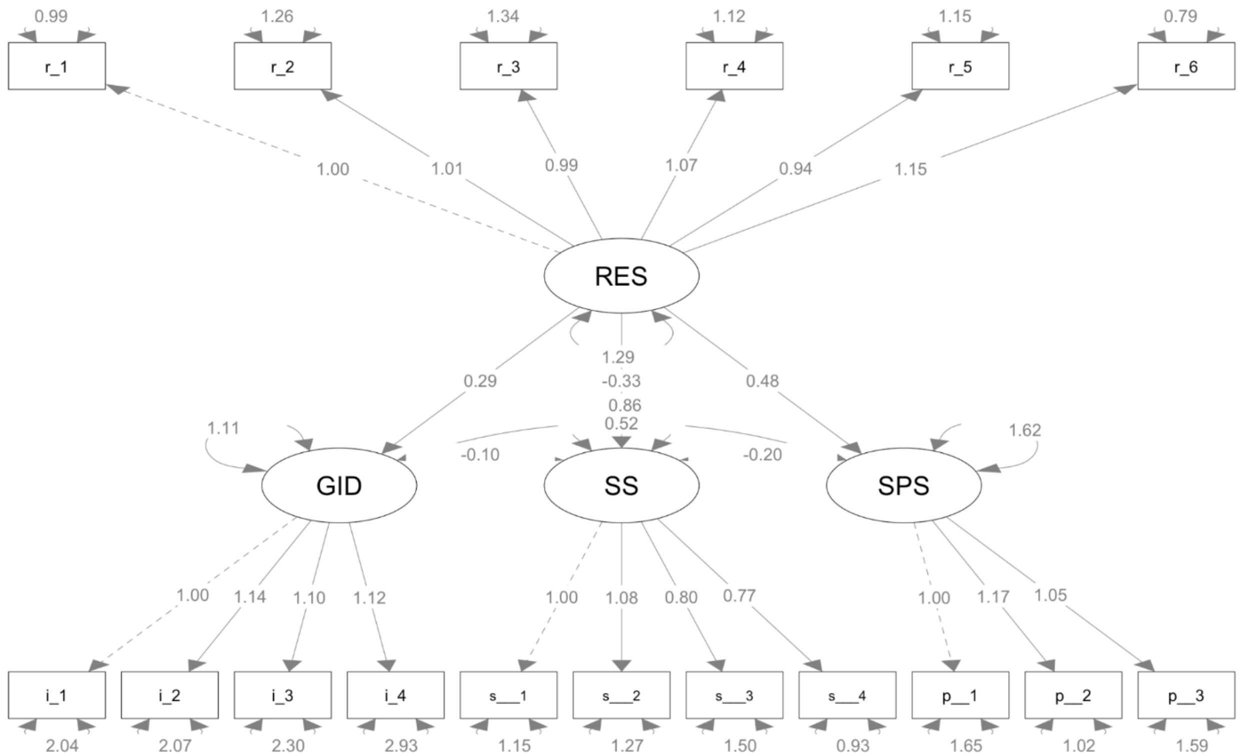
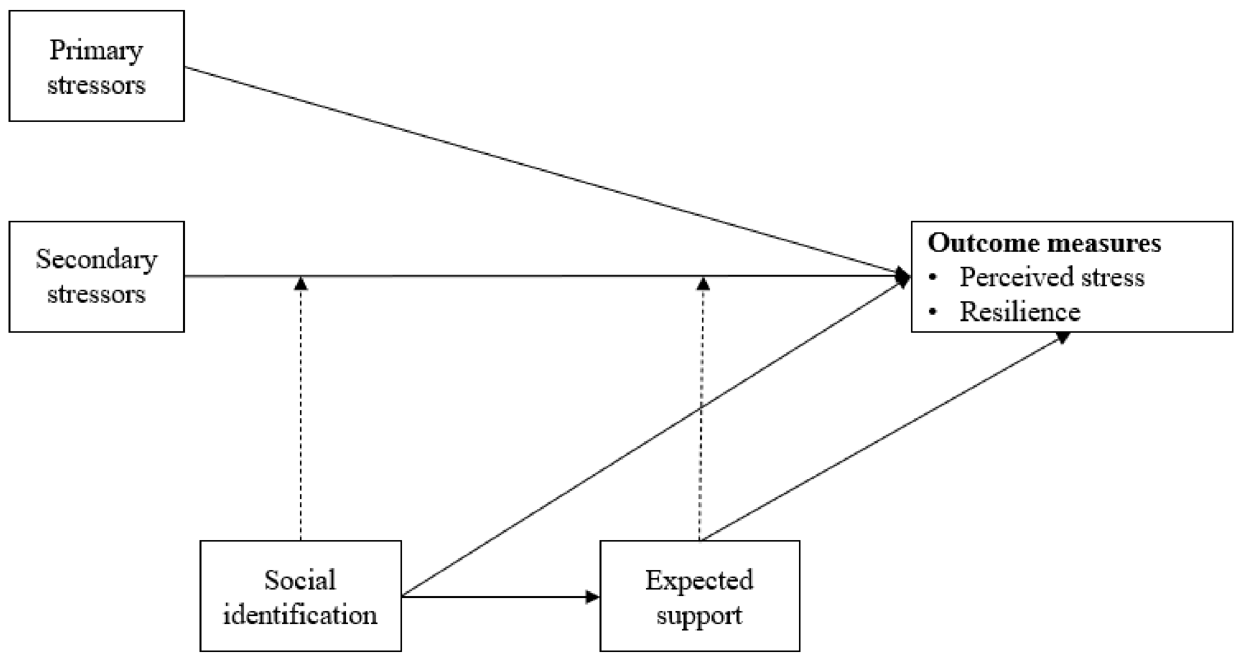


Figure S9. "Global" model that tests simultaneously all hypotheses described earlier in this paper.



Note: Demographics (SES and gender) were not included as moderators because previous analysis indicated that they did not exert any significant effects on the dependent variables. Expected social support was included as a moderator following reviewers' suggestions. Black solid lines indicate significant associations. Gray dotted lines indicate non-significant interactions. Statistical indicators can be found on Tables S6 and S7 on the supplementary materials.

Supplementary References

Chen, F. F., & West, S. G. (2008). Measuring individualism and collectivism: The importance of considering differential components, reference groups, and measurement invariance. *Journal of Research in Personality*, *42*(2), 259-294. https://doi.org/10.1016/j.jrp.2007.05.006

Guo, S. (2005). Analyzing grouped data with hierarchical linear modeling. *Children and Youth Services Review*, *27*(6), 637-652. https://doi.org/10.1016/j.childyouth.2004.11.017

Han, H., Dawson, K. J., Walker, D. I., Nguyen, N., & Choi, Y. J. (2022). Exploring the association between character strengths and moral functioning. *Ethics & Behavior*. https://doi.org/10.1080/10508422.2022.2063867

Li, C. H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, *48*(3), 936-949. https://doi.org/10.3758/s13428-015-0619-7

Lieberoth, A., Lin, S. Y., Stöckli, S., Han, H., Kowal, M., Gelpi, R., Flis, I., Sahin, H., Turk, F., Yeh, Y. Y., Ho, Y. W., Sikka, P., Delgado-Garcia, U., Lacko, D., Mamede, S., Zerhouni, O., Tuominen, J., Austin, T. B. & Dubrov, D. (2021). Stress and worry in the 2020 coronavirus pandemic: relationships to trust and compliance with preventive measures across 48 countries in the COVIDiSTRESS global survey. *Royal Society Open Science*, *8*(2), 200589. https://doi.org/10.1098/rsos.200589

Milfont, T. L., & Fischer, R. (2010). Testing measurement invariance across groups: Applications in cross-cultural research. *International Journal of Psychological Research*, *3*(1), 111-130. https://doi.org/10.21500/20112084.857

Muthén, B., & Asparouhov, T. (2018). Recent methods for the study of measurement invariance with many groups: Alignment and random effects. *Sociological Methods & Research*, *47*(4), 637-664. https://doi.org/10.1177%2F0049124117701488

Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review*, *41*, 71-90. https://doi.org/10.1016/j.dr.2016.06.004

Rouder, J. N., & Morey, R. D. (2012). Default Bayes factors for model selection in regression. *Multivariate Behavioral Research*, *47*(6), 877-903. https://doi.org/10.1080/00273171.2012.734737

Thompson, C. G., Kim, R. S., Aloe, A. M., & Becker, B. J. (2017). Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. *Basic and Applied Social Psychology, 39*(2), 81-90. https://doi.org/10.1080/01973533.2016.1277529

Wagenmakers, E. J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau, Q. F., Dropmann, D., Boutin, B., Meerhoff, F., Knight, P., Raj, A., van Kesteren, E. J., van Doorn, J., Smíra, M., Epskamp, S., Etz, A., Matzke, D., ... & Morey, R. D. (2018). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin & Review*, *25*(1), 58-76. https://doi.org/10.3758/s13423-017-1323-7

Westfall, J., & Yarkoni, T. (2016). Statistically controlling for confounding constructs is harder than you think. *PLOS One*, 11(3), e0152719. https://doi.org/10.1371/journal.pone.0152719