

Fortitude in the Face of a Pandemic Mediation Modeling to Characterize Resilience During COVID-19

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Abstract

Purpose

This study evaluated the differential impact of stressors and psychosocial resources on quality-of-life (QOL) outcomes, and investigated whether attitudes, perspectives, and behaviors relevant to wellness protect one from the negative and positive aspects of the coronavirus disease 2019 (COVID) pandemic.

Methods

This cross-sectional study done Spring/Summer 2020 recruited patients and caregivers of people with chronic medical conditions, and a nationally representative comparison sample of United States adults. Linear regression investigated the associations between COVID-specific variables and QOL outcomes, after covariate adjustment. Structural Equation Modeling investigated whether the links between Resilience and COVID-specific variables were mediated by attitudes, perspectives, and behaviors relevant to wellness.

Results

The sample seemed knowledgeable of and adherent to the practices endorsed by public-health experts. COVID-specific Hardship, Interpersonal Conflict, and Worry were associated with worse QOL outcomes, and Growth, Social Support, and Coping were associated with better. Wellness was the most salient predictor of Resilience, functioning both as a main effect and mediator for COVID-specific predictors. People with lower levels of Worry and/or higher levels of Social Support tended to have better-than-expected daily performance in the face of the pandemic. These two predictors acted in large part through the attitudes, perspectives, and behaviors relevant to Wellness.

Conclusion

Our findings support the idea that cultivating Wellness by dint of one's perspective, attitudes, and behaviors can be an important buffer to challenging times during a pandemic. Wellness seems to support resilience in its own right in addition to being a mechanism through which other factors can do so.

Introduction

We are living in extraordinary times. The novel coronavirus disease 2019 (COVID) has led to a world-wide health crisis that has required enormous changes in our lives. The social distancing needed to contain the pandemic has necessitated shutting down large portions of our economy, with important reverberations for livelihoods, healthcare, social connections, quality of life (QOL), and well-being. By dint of its different repercussions associated with sociodemographic and other personal characteristics [1–3], the novel coronavirus also presents a unique opportunity to study resilience to such multidimensional challenges.

The COVID pandemic presents stressors at many levels, including physical, emotional, social, and cognitive domains. The uncertainty and rapid pace of significant changes in people's lives renders this situation even more stressful. It is generally acknowledged that stress has a negative impact on health and well-being (e.g., [4, 5]). People can attenuate this impact by using coping strategies that are both behavioral (i.e., problem-focused) and cognitive, rather than by focusing on the negative and/or by venting (i.e., emotion-focused) [6]. Thus, even when dealing with a stressful and challenging situation, the way people think about it and behave can attenuate or exacerbate its impact.

The virus itself causes obvious physical challenges if one is infected, but it also impacts physical functioning by limiting one's ability to engage in normal activities, including exercise, if these activities involve being near or around other people. The pandemic causes emotional and social strain due to worry, hardship, social isolation, and interpersonal conflict due either to too much close contact among people with an already strained relationship, or due to difficulty coping with the imposed financial, logistic, or other hardships. The pandemic can cause cognitive strain, again due to worry, hardship, or other overwhelming situations. It would be useful to understand to what degree stressors of the pandemic are differentially associated with health and well-being outcomes.

A broad empirical literature suggests that health literacy is important to health outcomes [7]. In the context of COVID, these factors might include knowledge of and adherence to public-health recommendations for preventing viral spread, including wearing a mask, social distancing, hand-washing, etc. It would be useful to understand to what degree awareness of and adherence to these recommendations might be associated with better health outcomes.

Finally, in the face of the many negative aspects of the pandemic, what are the most effective ways of remaining resilient to its effects? Psychosocial research across many patient populations points to the importance of social support and social capital [8, 9]. In other words, having a network of people who provide companionship, emotional solace, fun, intellectual stimulation, and pragmatic assistance enables better functioning [10–12]. Choosing a proactive, other-centered approach can also help one to maintain a sense of optimism and agency [13, 14] in the COVID context. Research on altruism has documented clear mental-health benefits in general-population adults and teens [15, 16] and patient populations [6–8]. It has also documented physical-health benefits among females [15–17]. Altruistic behaviors have been posited to allow one to focus outside one's personal concerns, and thereby get a sense of perspective and even gratitude about one's own life challenges and resources [13, 18]. With COVID, a new set of ways of helping others emerges, including bringing food or medicine to others at greater risk than oneself, donating blood or money, helping with childcare, and reaching out to provide friendship and/or emotional support. In a world where social distancing is imposed for an unknown duration, these COVID-specific altruistic behaviors may have greater significance in conferring resilience.

All of these positive behavioral and attitudinal approaches may promote a type of wellness that potentiates resilience in the face of COVID. This conceptualization of wellness contains, but also goes beyond, four aspects: a way of being in the world that sees and embraces the good and expresses

kindness toward others (Outward View); a sense of engagement in one's activities and self-care (Self-Care/Calm); a downplaying of negative thoughts that reduce one's energy (Lack of Negativity); and an ability to feel joy or zest for life (Joy-Zest). The present study sought to evaluate the differential impact of the stressors and individuals' psychosocial resources on health and well-being outcomes, and to investigate whether the above conceptualization of wellness – a way of being in the world – protects one from the negative and positive aspects of the pandemic.

Methods

Design

This cross-sectional study was administered in late Spring through mid-Summer of 2020, as part of a larger, longitudinal study of the impact of the COVID-19 pandemic on health and well-being.

Sample and Procedure

This study recruited participants via Rare Patient Voice, LLC and Ipsos Insight, LLC –the former to target patients and caregivers of people with chronic medical conditions; the latter to target a comparison sample of United States (US) adults, nationally representative in terms of age distribution, gender, region, and income. Eligible participants were age 18 or older and able to complete an online questionnaire. Participants with motor, visual, and/or other problems that made it difficult for them to complete the web-based survey instrument enlisted the assistance of someone else to enter the participant's answers. Individuals with severe cognitive impairment were ineligible. This survey was administered through the secure Alchemer engine (www.alchemer.com), which is compliant with the US Health Insurance Portability and Accountability Act. The protocol was reviewed and approved by the New England Independent Review Board (NEIRB #2021164), and all participants provided informed consent prior to beginning the survey.

Measures

COVID-Specific Questions included selected items compiled by the US National Institutes of Health Office of Behavioral and Social Sciences Research and the NIH Disaster Research program [19]. These items assessed infection status, COVID-specific literacy, self-protective steps, perceived risk-taking behavior, hardship (including financial lack, homelessness, and disruption of healthcare), COVID-specific altruism, social support / isolation, positive and negative coping, substance use, interpersonal conflict, and four items adapted with permission from the Post-Traumatic Growth Inventory [20–22]. (See Supplemental Table 1 for items used.)

Health-Related QOL was assessed with standardized tools appropriate for use across all populations. The PROMIS-10 is a brief measure of general physical and mental health [23]. The NeuroQOL Applied Cognition [24] is a brief measure of perceived difficulties in everyday cognitive abilities (memory,

attention, and decision-making) and in applications of mental function (planning, organizing, calculating, working with memory and learning).

Well-Being was assessed using the NeuroQOL Positive Affect and Well-Being short-form [24] and Ryff Psychological Well-Being Scale subscales for Purpose in Life and Environmental Mastery [25, 26]. These subscales have documented reliability and validity [25, 26].

Related to but distinct from the above measures of well-being, the *DeltaQuest Wellness Measure*® (DQ Wellness) is a recently validated 15-item measure tapping attitudes, perspectives, and behaviors relevant to wellness [27]. Thirteen positively-worded items assessed concepts such as joy/zest, self-care/calm, and outward view (i.e., a positive engagement in the world and with others). Two negatively-worded items tapped characteristics antithetical to wellness, namely low energy, and a preoccupation with the negative aspects of one's life. All items followed an instruction to "indicate how true each of the following statements is for you over the past week" and used rating-scale descriptors ranging from "not at all" (0) to "very much" (4). All items provided an option "do not know/prefer not to answer." The measure best fit a bifactor model, with one General Wellness score and four specific factors (Outward View, [Lack of] Negativity, Self-Care/Calm, and Joy/Zest). Using the current sample, we validated the measure in terms of cross-sectional reliability, general construct validity, convergent and divergent validity, and known-groups validity [28]. It has also demonstrated negligible differential item function [29] by gender.

Resilience was assessed using the Centers for Disease Control Healthy Days Core Module [30] (see Statistical Analysis below). In this measure, two items ask how many days of the past 30 the respondent's physical health (Physical Health Problems) or mental health (Mental Health Problems), respectively, was not good. A third item, Activities of Daily Living Impaired (ADL Impaired) asks in how many of the past 30 days these health problems kept them from doing their usual activities, such as self-care, work, or recreation.

Demographic characteristics included year of birth, gender, with whom the person lives, cohabitation/marital status, ethnicity, race, country of parents' origin, height, weight, difficulty paying bills, employment status, education, occupation, smoking status, year of chronic medical diagnosis (if applicable), comorbidities, disease category, and whether the participant received help to complete the survey. Occupational complexity was assessed using questions querying the job that was closest to the respondent's current or past reported occupation, which were then scored for complexity using the Occupational Information Network (O*NET) system [31]. Under this comprehensive, in-depth job-classification system, complexity scores range from low [1] to high [5]), with higher scores reflecting more training and skills required to perform that occupation [32].

Statistical Analysis

Descriptive statistics summarized the sample demographic characteristics and scores on person-reported outcomes. We used wave analysis [33] to assess selection bias by correlating 23 key variables with date of survey submission. COVID-specific variables were grouped by content and summarized via means of

related item sets. For COVID infection status, an Ambiguity score was devised on the basis of degree of agreement across three sources of information: (a) COVID test; (b) healthcare provider's assessment; and (c) participant's self-assessment. This Ambiguity score could take values of 0, 0.5, 1, or 2; 0 indicated that all sources agreed on whether the person had been infected, and 2 showed direct contradiction between different sources. As an attempt to assess the role of infection status most sensitively, this Ambiguity variable was included as a main effect and in an interaction term with COVID status in linear regression models described below.

Multivariable linear regression was used to investigate the associations between COVID-specific variables and QOL outcomes, after adjusting for the following demographic characteristics: age, gender, body mass index, occupational complexity, and number of comorbidities.

To operationalize Resilience in the mediation structural equation models (SEM), we built on a precedent for using residual modeling to infer Resilience based on the behavior of other variables in the model [34–36]. This approach has been used in multiple studies of chronically-ill people and their caregivers [37–39]. The method involves regressing the CDC Healthy Days ADL Impaired on Physical Health Problems, Mental Health Problems, and their interaction. The residuals from the regression model were saved and multiplied by negative one (-1). Thus, a high Resilience score reflects “over-performance,” or more days than expected that the respondent was able to function despite physical or mental health problems or their synergistic effect [18]. Similarly, a low Resilience score reflects “under-performance.” Further, in a separate use of residual modeling, our mediation analysis to predict Resilience employed a version of it that had first been regressed on (adjusted for) eight demographic and health-related variables: education level, age, gender, race, Hispanic ethnicity, body mass index, number of comorbidities, and number of comorbidities squared.

Structural Equation Modeling (SEM) was then implemented to investigate whether the links between Resilience (dependent variable) and COVID-specific variables (independent variables) were mediated by attitudes, perspectives, and behaviors relevant to wellness (as captured by the DQ Wellness Measure). We tested General Wellness as the mediator for several reasons. First, it assesses individual-difference variables that are likely amenable to modification and intervention. Thus, if results affirm its meaningfulness in promoting resilience, they might motivate psychosocial interventions to help people be more resilient in the face of the pandemic. Second, using the DQ General Wellness score rather than the four specific factor scores enhanced model parsimony and interpretability. The General Wellness score (hereafter simply Wellness) has high marginal reliability [40] of 0.89, and summarizes the inter-item relationships well (explains 58% of the variance in the 15 items) [27]. Finally, this score reflects complex content related to wellness, rather than more circumscribed content as would be the case with the Ryff Purpose in Life and Environmental Mastery subscales.

We began building the SEM investigating whether we could group the positively- vs. negatively-oriented variables together as part of latent constructs of “support” and “stress,” respectively. Our results indicated that variables within each set were not highly correlated with each other (see Supplemental Table 2),

leading to poor reliability. Fit statistics were also unsatisfactory. Therefore, all positively-oriented and negatively-oriented variables were entered into the model as separate indicators in subsequent models. We did not include COVID-specific Growth in the SEM because it would be too closely related to the concept assessed by Wellness.

In order to hone the SEM predictors further, a hierarchical series of models tested simple mediation effects (i.e., one independent variable, Wellness as mediator, resilience as outcome). To test the effect of COVID status, we compared model-fit statistics using COVID status as a covariate versus separate mediation models for those infected and not infected.

IBM SPSS version 27 [41] and Mplus version 8.4 [42] were used for all analyses.

Results

Sample

The study sample included 3,085 patients, 685 caregivers, 191 patient/caregivers, and 855 in the comparison group (Total N=4,816). The sample was heterogeneous across age, gender, socioeconomic status, health status, and US geographic region. Table 1 provides sociodemographic characteristics and the most prevalent disease categories. The sample had a mean age of 51.6 (standard deviation [SD] = 14.2), and 82% were female. The sample race was 89% white, 6% black, and 4% other; ethnically, 5% were Hispanic. Sixty-two percent of respondents were married or in a domestic partnership, and 12% were living alone. With regard to selection bias, wave analysis produced 23 coefficients with $-0.12 < r < 0.13$; the mean r was 0.02 and, in absolute terms, 0.05, with only four of 23 coefficients exceeding 0.10. Thus, earlier and later respondents were similar in all of these respects, suggesting that non-respondents would have been as well.

In the sample, 380 people (8%) indicated that they had been infected with COVID (Table 1). For 11% of the sample, their COVID-infection status was based on complete agreement among sources (i.e., doctor, test, patient). For 87%, this status was slightly ambiguous, such as when relying on one “definite” but also one “probable” finding or non-finding. Given the difficulty procuring COVID tests during the baseline data-collection period, this ambiguity was expected. Table 2 provides the descriptive statistics of the person-reported outcomes (PRO) and COVID-specific variables. The skewed distributions for Protection and Risk behavior suggest that the sample overall largely followed guidelines for reducing possible exposure to the virus (Table 2). Most people reported low levels of Interpersonal Conflict and Hardship, although both of these distributions had long tails and non-trivial numbers of people with high scores. Growth, Altruism, Social Support, Worry, and Coping had non-skewed distributions that covered a broad range of scores.

Association of COVID-specific variables with outcomes

Eight regression models are summarized in Table 3, and bivariate correlations in Supplemental Table 3. Effect sizes (ES) for standardized regression coefficients (β) are indicated with conditional formatting

(i.e., more saturated highlighting indicates larger ES; see table legend). These models revealed that the following COVID-specific variables were not strongly associated with any of the PROs studied: COVID infection status, ambiguity of infection, their interaction, Literacy, Protection, Risk-Taking, and Altruism. COVID-specific hardship was associated with worse Physical Health, Applied Cognition, Environmental Mastery, and Resilience. Growth and Social Support were associated with better Mental Health, Positive Affect, Purpose in Life, Environmental Mastery, and Wellness. Interpersonal Conflict and Worry were associated with worse Mental Health, Applied Cognition, Positive Affect, Purpose in Life, Environmental Mastery, Wellness, and Resilience. COVID-specific Coping was associated with better scores on all outcomes. The explained variance after adjusting for number of variables in the models ranged from 31% to 51%, all of which were large effect sizes using Cohen's criteria [43].

Comorbidities constituted a prominent predictor of worse scores on all of these outcomes, and particularly on Physical Health and Resilience. In contrast, squared comorbidities was an important predictor of *better-than-expected* scores on nearly all of these outcomes after accounting for the linear effect. This latter term was included based on diagnostic plots which suggested a strong quadratic component for comorbidities in each such relationship.

Table 4 and Figure 1 show results of the final SEM mediation model. This model explained a substantial portion of the variance in Resilience ($R^2=0.23$); it included as independent variables Hardship, Interpersonal Conflict, Worry, Altruism, Coping, and Social Support. Analysis revealed significant direct effects on Resilience of Hardship, Interpersonal Conflict, Worry, and Social Support, as well as a significant direct effect of Wellness, which had, at 0.36, the strongest coefficient in the solution. These six COVID-related predictors had significant indirect effects on Resilience mediated by Wellness. The largest indirect effect was for Worry at -0.10. For these six predictors, total effects (the sums of direct and indirect coefficients) were strongest for Worry (-0.20) and Social Support (0.15). The model fit was very good (RMSEA=.043, CFI=.998, and TLI=.968), using Hu and Bentler's criteria [44]. COVID infection status was not a significant predictor of Resilience ($p=0.70$).

Discussion

The present study demonstrated that COVID-specific Hardship, Interpersonal Conflict, and Worry were associated with worse QOL outcomes, and Growth, Social Support, and Coping were associated with better. The mediation-model results revealed that Wellness was the most salient predictor of Resilience of all of the variables considered. Wellness functioned as both a main effect and as a mediator for six other predictors. Of these, Worry and Social Support showed the strongest total effects. People with lower levels of Worry and/or higher levels of Social Support tended to have better-than-expected daily performance in the face of the pandemic. These two predictors seem to have acted in large part through the attitudes, perspectives, and behaviors relevant to Wellness. Such mediated connections were found to be statistically significant for the other predictors as well, but with decreasing strength of total effects as we considered Interpersonal Conflict, Coping, Hardship, and Altruism, respectively.

The present study also provides useful descriptive information about general knowledge and habits related to COVID protection/risk behavior in the United States during the first five months of the pandemic. Despite confusing and contradictory messages from various leaders about best practices for self-protection, the people in our sample seemed knowledgeable of and adherent to the practices endorsed by public-health experts. This is heartening information, particularly given the multiple-comorbidity profile of many participants. It is worth noting, however, that a lower-literacy sample would find it more challenging to disentangle the contradictory public messaging around COVID protection/risk behavior.

Multiple comorbidities were associated with worse outcomes to a point, but after that point, outcomes were no worse and sometimes slightly better, reflected by the strong positive quadratic coefficient for comorbidities. For example, Physical Health was increasingly worse for people with one to five comorbidities, but plateaued for those with more comorbidities. This pattern suggests another manifestation of resilience, which could be called a “threshold for habituation”: people in this sample are increasingly able to manage health conditions as the latter become more numerous.

While our study has clear advantages in terms of large sample size, collection of a comprehensive set of informative variables about COVID, and careful modeling, its limitations must be acknowledged. First, the participants were disproportionately female, and Blacks and especially Hispanics were under-represented. Second, it is not possible to calculate a response rate given the participant-recruitment sources, so the generalizability of the findings is unknown. Nonetheless, concerns about selection bias may be allayed by the minimal evidence of such bias from the wave analysis. Additionally, the Ipsos comparison sample was specifically recruited to be representative of the adult population in the United States. Based on the sample’s COVID-related Literacy scores, it seems results would generalize best to those fairly well-educated about the virus. Third, the COVID-specific measures are based on recommended individual items from the National Institutes of Health rather than scales developed from rigorous psychometric testing. It is thus possible that the scales are not as reliable and valid as they might be in less urgent circumstances. Variables representing COVID-related literacy and risk-taking may not have been retained in the SEM of resilience and may have produced weak coefficients in regressions with other PROs (Table 3) because their skewed distributions and/or low alpha reliabilities attenuated relationships [45]. Observed relationships involving Worry, Coping, Social Support, and Altruism may also have been limited by such attenuation. Finally, the mediation models are built from cross-sectional data, and so any causal inference is limited. Future research might assess causality using similar models fashioned from longitudinal data.

Our findings support the idea that cultivating Wellness by dint of one’s perspective, attitudes, and behaviors can be an important buffer to challenging times during a pandemic. Wellness seems to support resilience in its own right in addition to being a mechanism through which other factors can do so. Enhancing this type of Wellness may dovetail with the goals of mindfulness [46] and other successful psychosocial interventions [47,48,22]. It is our hope that this study will facilitate pragmatic guidelines to help people cope with this pandemic.

Abbreviations

COVID = coronavirus disease 2019

ES = effect size

O*NET = Occupational Information Network

PRO = person-reported outcome

QOL = quality of life

SD = standard deviation

SEM = structural equation modeling

US = United States

Declarations

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Availability of data and material. The study data are confidential and thus not able to be shared.

Code availability. Requests for software code will be considered, and will be made available if deemed reasonable.

Authors' contributions. CES, RBS, and BDR designed the research study. CES, RBS, and KB analyzed the data. CES wrote the paper and RBS, KB, and BDS edited the manuscript. All authors read and approved the final manuscript.

Ethics Approval. This study was conducted in accordance with the provision of the Declaration of Helsinki. The study was approved by the New England Independent Review Board (NEIRB #2021164).

Consent to participate. All the patients provided written informed consent before participation.

Consent to publish. All participants agreed to their data being published in a journal article.

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Tables

Due to technical limitations, table 1, 2, 3 and 4 is only available as a download in the Supplemental Files section.

Figures

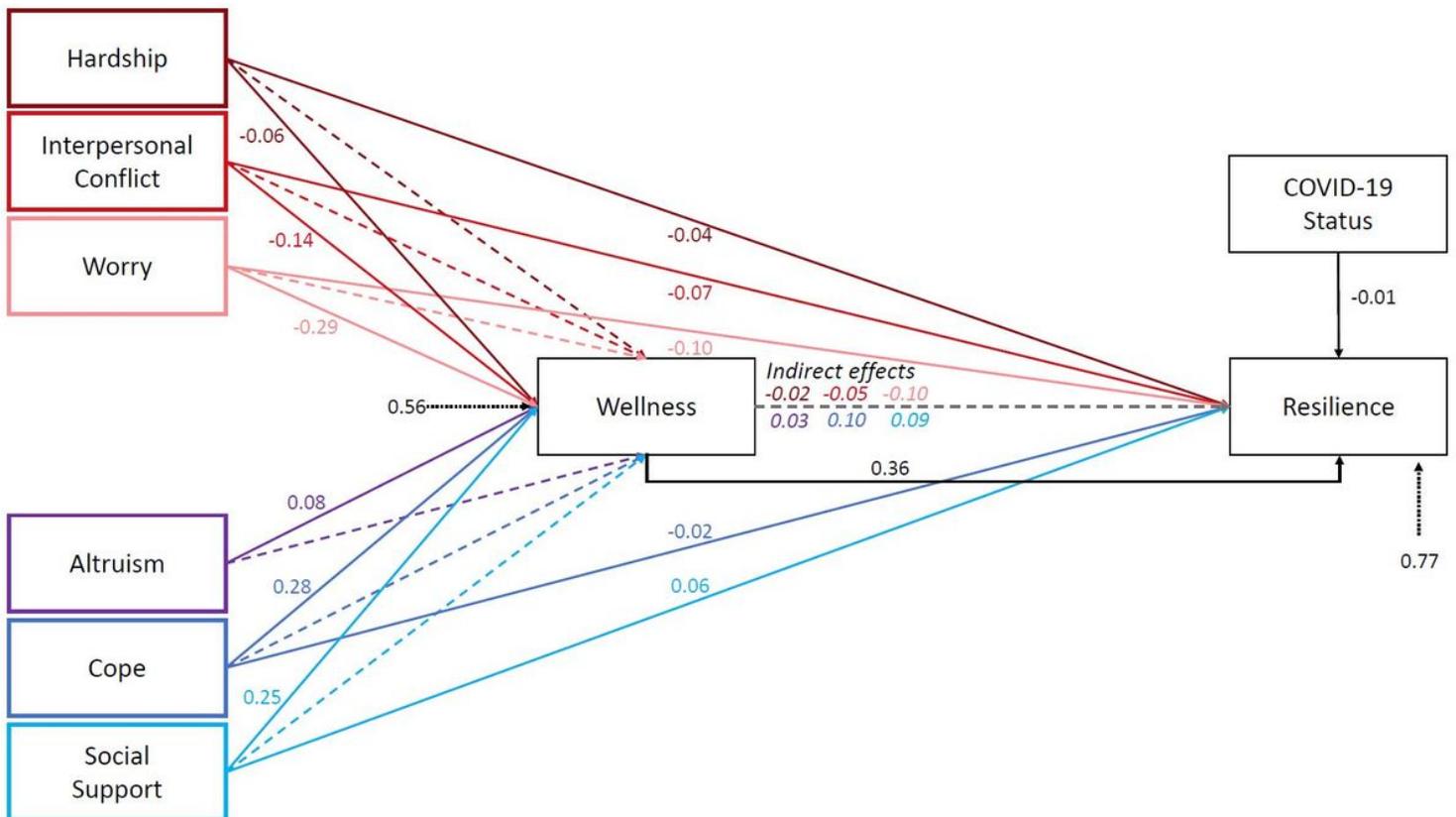


Figure 1

The Full SEM Mediation Model. This model revealed significant direct effects of Wellness and of COVID-related Hardship, Interpersonal Conflict, Worry, and Social Support on residualized Resilience (i.e., adjusted for eight demographic and health-related variables). It revealed significant indirect effects of Hardship, Interpersonal Conflict, Worry, Coping, Social Support, and Altruism on Resilience. The model fit was very good (RMSEA=.043, CFI=.998, and TLI=.968). COVID infection status was not a significant

predictor of Resilience ($p=0.70$). This model supports the hypothesis that the relationships linking resilience with COVID-specific stressors and supports are mediated by Wellness – a way of being in the world that provides a sense of perspective, positive attitudes, and self-care behaviors.

Supplementary Files

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- [SchwartzCOVIDResilienceMediationSuppTables.pdf](#)
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