A Componential Model of Stress Reactivity in Daily Life

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Abstract

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Despite widespread agreement about the importance of stress for health and well-being, scholars disagree about the types of variables that matter most. On one side, some argue that stress reactivity depends mostly on person-level variables, such as personality, while others contend that stress reactivity depends mostly on situation-level variables, for example chronicity. Researchers from a more integrative perspective assert that stress reactivity depends on an idiosyncratic interaction between person-level and stressor-level variables, for example the finding that lonely people are especially reactive to interpersonal tension. My dissertation reconciles these perspectives by leveraging crossed random effect modeling to determine the percent of stress reactivity attributable to each of these types of variables; the person, the situation, and the person-by-situation interaction. In Study 1, 368 undergraduate college students reacted to 60 unique situations in the context of normal daily life on two separate occasions. In Study 2, 955 adults from the Midlife in the U.S. study self-reported their reactivity to stressful situations encountered on each of eight days. Results from both studies suggest that these three types of variables account for the bulk, at least 70%, of stress reactivity in daily life. Moreover, all three types of variables emerged as important, as each factor contributed at least 20% of the overall variability in stress reactivity. Interestingly, both studies also found that situation-level variables mattered relatively more than the other two types of variables. I discuss these findings in relation to stress theory, stress-reduction interventions, and methodological innovations.

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Dedication

To the people of New York, who have taught me more about psychology than any textbook.

Preface

Stress has become a ubiquitous part of American life. Use of the word ‘stress’ has grown almost exponentially since 2000 according to a representative selection of over 40 million books, as seen in Figure 1. This increase is not a linguistic artifact. An analysis of more than 2,000 U.S. adults between 1995 and 2014 found that people experienced an extra week of stressful days per year in the 2010s relative to the 1990s (Almeida et. al, 2020). Since the emergence of the coronavirus pandemic, Americans report being more stressed than any other time in recent history (APA, 2020).

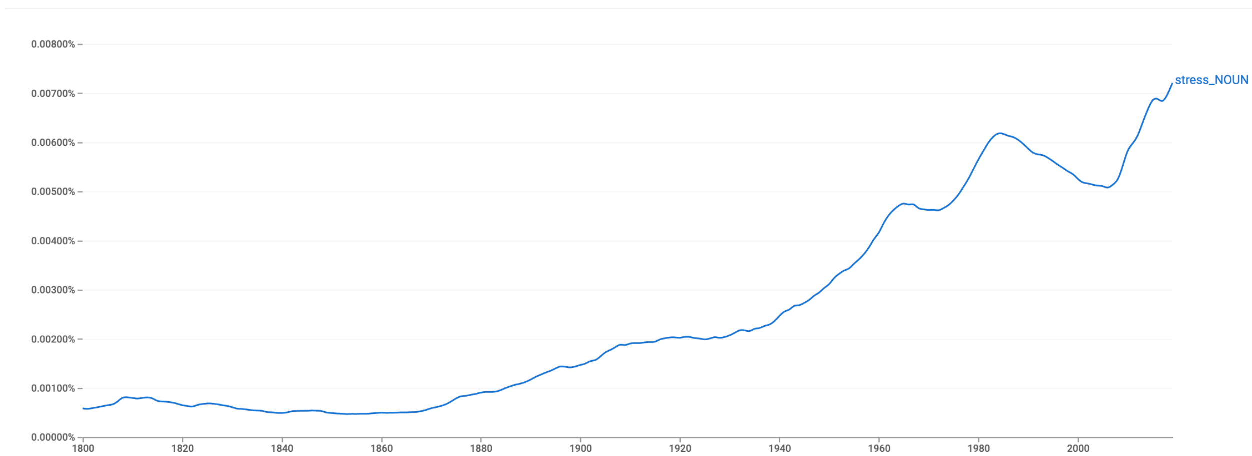

Figure 1: Google Books Ngram for “Stress”

This surge in stress is problematic insofar as stress negatively affects psychological and physical health. Psychologically, stress can lead to clinical levels of depression and anxiety, while physically stress can lead to cardiovascular disease, infection, and cancer (Cohen et al., 2007). Researchers therefore consider stress a major risk factor for morbidity and mortality (Epel et al., 2018). Because of this, the National Institutes of Health—the U.S. government’s largest funder of scientific research—has invested nearly $2 billion in psychological stress research in the last two decades (NIH RePORTER).

Because of this, thousands of studies now explicate variables that each, in part, explain why a person experiences stress. The aim of my dissertation is to conceptually and empirically synthesize this vast literature using a novel application of crossed random effect modeling. Conceptually, I will argue that the bulk of prior scholarship on stress can be binned into one of three categories. The first reflects a personality psychology perspective, a focus on how differences between people explain stress, i.e., how neurotic people experience more stress relative to their non-neurotic counterparts (Bolger & Schilling; Mroczek & Almeida, 2004; Wrzus et. al, 2021). The second category reflects a more social psychological perspective, a focus on how differences between situations give rise to more versus less stress reactivity, i.e., how chronic situations are more stressful for everyone relative to acute situations (Gannon & Pardie, 1989). The third and final major category reflects a clinical, psychodynamic perspective, a focus on how certain people are trigged by certain situations, i.e., how receiving bills is particularly stressful for people who are financially poor (Davis & Mantler, 2004). In my dissertation, I will emphasize how binning prior studies into these categories enables us to look beyond the specific variables that contribute to stress and instead consider the *types* of variables that are most important. In these preliminary investigations, I will focus only on daily stressful events, the minor "hassles" that affect people's everyday lives such as interpersonal conflict, child-care, and home maintenance. This work will lay a roadmap for the daily stress literature, one that empirically shows the relative importance of scientific perspectives on stress science as well as identifies key areas for future interventions.

This work fits nicely into my prior graduate school research. I entered graduate school broadly interested in how social relationships influence stress processes and vice versa. I was also eager to learn how statistics could help answer age-old questions in this domain in new ways. In my first publication on the topic, I built a novel theoretical and statistical framework that integrated prior scholarship on the effects of stress on relationship cognitions within romantic dyads. In that paper (Goldring & Bolger, 2019), I found that one partner's stress not only shapes how their own judgment of their relationship, but also the partner's judgment of the relationship. The dyadic nature of stress and relationship cognitions was attributed to both intra-individual mechanisms—a stressed partner directly influences how their romantic partner views the relationship—and interindividual mechanisms—a stressed partner stresses out the other partner, and the second partner's stress shapes their own judgments.

In another line of work, I flipped this, investigating how social relationships shape stress reactivity. In one psychophysiology experiment with newly acquainted dyads and one daily diary study with romantic dyads, my colleagues and I found that the psychological experience of shared reality reduces reactivity to stressful situations, and that this effect is especially pronounced for females (Goldring et al., in press). These findings imply a psychological mechanism, shared reality, that may underlie the tend-and-befriend response that characterizes female's reduced reactivity to stressful situations when social bonding is achieved.

As I was learning more about interpersonal relationships and stress, I became increasingly interested in stress on its own; how it operates, what it leads to, and how it is conceptualized. In reading the literature on the psychological and physical outcomes of daily stressors, I realized that existing scholarship was siloed and required an integrative theoretical and statistical model to clarify discrepancies and introduce novel findings based on classic stress theory. I learned about and applied an under-utilized statistical model, a non-recursive structural equation model, to shed new light on the effects of daily stressors (Goldring & Bolger, 2021). I found that psychological distress mediates the relation between stressors and physical symptoms for the average person, that the relations are bidirectional (psychological distress leads to more daily stressors and physical symptoms leads to greater psychological distress), that even though bidirectional associations exist feedback loops do not exert large effects, and that all of these processes are not only highly heterogenous between people, but also non-existent for some and operate in reverse directions for others.

I have also aided in the development of new statistical models related to the ones used in my dissertation (Kenny et. al, 2021), applied novel statistical models to questions about health behaviors (Marcum et. al, 2017), branched outside of my discipline by studying how social group-based information shapes moral judgments about health behaviors (Goldring & Heiphetz, 2020), and contributed to a productive program of research on how genomic information shapes people's health behaviors for themselves and others (Goldring & Persky, 2018; Marcum et. al, 2018; Persky et al., 2017, Persky et al., 2019).

My dissertation is therefore a culmination of years of learning and growing as a researcher and statistician. By better understanding the composition of stress reactivity for daily stressors among college students and U.S. adults, I hope that this work contributes to smarter stress-reduction interventions, more sophisticated statistical applications, and greater understanding of stress in daily life.

Chapter 1: Introduction

Americans experience more daily stressors in the 2020s than any time in recent history (American Psychological Association (APA), 2022). In response, the APA has published several call-to-actions; for example, one APA op-ed suggested five ways for Americans to reduce daily stress reactivity; they should “make themselves” remain calm, focused, relaxed, grounded, and celebrated (APA, 2021). These proposed solutions assume that stress reactivity depends on person-level variables; if only a person changes their outlook on life (e.g., Mackenzie et. al, 2007), the way they react to situations (e.g., Limm et. al, 2011), or how they view specific events (e.g., Mathhieu & Ivanoff, 2006), then stress reactivity can be reduced. This person-centered approach dates back to some of the earliest and most influential research in stress psychology (Hobfoll, 2004). In a famous debate on the topic, Lazarus and colleagues (Lazarus et. al, 1985) asserted that stress reactivity depends entirely on a person’s reaction to a situation. Therefore, there is no such thing as an objectively stressful situation (Lazarus, 2006). However, Dohrenwend and colleagues (1984) asserted that stressful situations are measurable events. To Dohrenwend et. al, some situations are simply stressful, regardless of how mindful or calm the person is. Lazarus and Dohrenwend, at face value, debated measurement. But their disagreement reflected a deeper philosophical question in the stress literature: Is a person’s level of stress reactivity explained by who they are or the situation they are in?

How a researcher answers this question fundamentally shapes the type of research they do; in contemporary stress research, personality psychologists tend to study how person-level variables (i.e., neuroticism) explain stress reactivity while social psychologists tend to study how situation-level variables (i.e., uncertainty) explain stress reactivity (for a broad overview beyond the stress literature, see Reis & Holmes, 2012). However, an either/or view on stress reactivity belies the true nature of the construct. Scientific findings are necessarily contextualized, always existing from some perspective that elucidates only partial truth (McGuire, 2004). Only by creatively generating hypotheses that simultaneously consider many viewpoints can full knowledge be obtained (McGuire, 1997). Perhaps stress reactivity is not a function of who a person is *or* the situation they are in, but instead a function of both. Instead of asking "does the person or situation elicit stress reactivity", perhaps I can ask "how much of a person's stress reactivity is because of who they are and how much is because of the situation they are in?"

The existing literature provides seemingly contradictory answers. A recent study by Dohrenwend et. al (2013) found that 72% of a sample of Vietnam war veterans developed post-traumatic stress disorder (PTSD) after exposure to highly threatening combat. Included in that number were individuals with low vulnerability to pathology. These results imply the importance of both situation and person, since exposed individuals were far more likely to develop pathology relative to the general population but were not necessarily destined to do so. The large proportion who developed PTSD signifies the relative dominance of the situation in a context where both person and situation matter. However, the proportions were almost reversed in Bonanno et. al's (2010) investigation of PTSD among New Yorkers exposed to 9/11, where only 30% of exposed individuals developed clinical levels of depression or PTSD. These results again imply the importance of both person and situation but instead emphasize the relative dominance of the person; only some people developed PTSD and those who did were distinguished by their demographic and vulnerability (i.e. person-level) characteristics (Bonanno, 2007). In the context of highly traumatic situations, the relative importance of the person and situation remains unclear.

There are several reasons for the lack of clarity. The primary reason is that neither of these studies, nor any in the existing stress literature for that matter, were designed to reveal the relative importance of person and situation in stress reactivity. Prior studies document the proportion of *people* who exhibit reactivity to stressful situations, rather than the proportion of *reactivity* that is attributable to who those people are versus the situations they are in. Partitioning reactivity into person and situation components requires a new methodology, one that I introduce in this paper. I do so in the context of daily stressors, which are minor hassles that almost everyone experiences in daily life (Almeida, 2004) and psychological reactivity, defined as changes in mood following a stressful stimulus. Daily stressors and subsequent psychological reactivity are an appropriate context for a preliminary investigation of the relative importance of person and situation because of their implications for long-term health. Self-reported mood in response to daily stressors reduces heart rate variability (Sin et al., 2016), increases biomarkers related to inflammation (Sin et al., 2015), predicts chronic physical health conditions later in life (Piazza et al., 2013), and even potentiates earlier death (Mroczek et al., 2015). Moreover, daily stressors, by definition, occur to every person at some level of regularity (Almeida, 2020). Understanding the proportion of stress reactivity attributable to person and situation can provide a useful roadmap for important intervention studies.

Beyond the person and situation, there are other major factors that influence stress reactivity, most obviously the person-by-situation interaction. The terminology 'person-by-situation interaction' has taken on different meanings in prior scholarship, and I focus on the diathesis-stress version here. The diathesis-stress version refers to the fact that certain situations trigger reactivity among certain people (Johnson & Johnson, 2010). Often touted in the clinical literature, and famously by Walter Mischel & Yuichi Shoda (1995), studies in this domain investigate how people bring their own vulnerabilities into certain situations. For example, one study found that individuals high in self-concept differentiation were most reactive to network stressors while individuals low in perceived control were most reactive to home stressors (Hay & Diehl, 2010). Table 1 summarizes these three components of stress reactivity, components that I believe cover the majority of the literature on stress reactivity.

Table 1: Existing Theoretical Perspectives in the Stress Literature

Theoretical Perspective	Definition	Conceptual Example	Example Papers
Person	Stress reactivity depends on stable features of who a person is. Regardless of the situation, some kinds of people exhibit heightened reactivity relative to other kinds of people.	Because Abi is highly neurotic, he always reacts strongly to stressors, even stressors that seem benign to other people.	Bolger & Zuckerman, 1995 Bonanno, 2021 Costa et. al, 1996 Ip et. al, 2021 Kobasa, 1979 Lee-Flyn et. al, 2011 Noser et. al, 2014
Situation	Stress reactivity depends on stable features of a situation. Regardless of the person, some situations are simply more stressful than others.	Because interpersonal conflicts alter how people think of themselves and others, interpersonal conflicts elicit reactivity for almost all people.	Brown, 1974 Holmberg et. al, 2011 Holmes & Rahe, 1967 Greco & Roger, 2003 Scott et. al, 2013
Person-by-Situation	People are uniquely triggered by certain environments. Stable features of who a person is can interact with particular types of situations, which elicits reactivity for that person and situation combination.	Because Roysi has high shared reality needs, she reacts strongly to all interpersonal conflicts and because James has low shared reality needs, he reacts strongly to other types of stressors, in his case financial stressors.	Colodro-Conde, 2018 Felston & Wilcox, 1992 Russo et. al, 1995

Our goal now is to determine the proportion of stress reactivity that is attributable to these three components. Our method for doing so was inspired by the Social Relations Model (SRM) in the person perception literature (Kenny, 1994; 2019). The SRM is simply a crossed random effect model, which is implied by data wherein multiple people react to multiple different daily stressful situations. I believe this is most easily understood with a simple example. Suppose that three people react to four situations and that their reactivity to each situation is measured from 0 to 4, with 4=extremely reactive. The data might resemble what is seen in Table 2.

Table 2: Hypothetical Data for a Crossed Random Effect Study Design

	Roommate Trouble	Argument	Broken Computer	Late Bus	Row Means *(~p_i)*
Alex	2	4	3	1	2.5
Drew	3	2	1	1	1.8
Jordan	3	1	2	3	2.3
Column Means *(~s_i)*	2.7	2.3	2.0	1.7	Grand Mean: 2.2

The idea is that variance in the cell values implies a total amount of variability in stress reactivity. The model decomposes that total amount of stress reactivity variability into person, situation and person-by-situation variability. Look first at the row means. Notice that Alex has higher mean stress reactivity than Drew. Perhaps Alex is neurotic (Bolger & Schilling; Mroczek & Almeida, 2004; Wrzus et. al, 2021), from a low socioeconomic status (Grzywacz et. al, 2004; Neupert et. al, 2006), or perceives little control over their own life (Wen & Sin, 2021). Regardless of the specific person-level variable that explains why, the greater the difference (i.e., variability) between people in the row means, the greater the importance of those kinds of variables. Consider now the column means. Variability by column means implies the importance of the situation in explaining stress reactivity. Notice that the roommate problem elicits more reactivity than the late bus across persons, depicted in the column means for those situations. Perhaps the roommate problem requires more adjustment for the average person or elicits more distress (Brown & Harris, 1989). The level of variability between situations signals their importance.

Determining the relative importance of the person-by-situation interaction requires another instantiation of Table 2, a replication (Kenny, 1994). Suppose that the three participants were invited on a second occasion to react to the same four situations. If Alex again rated the roommate problem as more stressful than the argument while Drew rated the argument as more stressful than the roommate problem, then there must be something particular about Alex and the roommate problem, as well as Drew and the argument, that triggers reactivity. The extent to which people and situations vary in this way over time signals the extent to which these types of effects are important.

Formally, the data structure depicted in Table 2 is a half-block crossed random effects design. Assuming a few statistical assumptions, this implies that stress reactivity for person *i* experiencing stressor *j* at instance *k* (the cell value, X_{ijk}) is a linear function of a constant (*c*), person-level factors (p_i, conceptually similar to the row means and calculated by subtracting the grand mean from the row mean for each person), stressor-level factors (s_j, conceptually similar to the column means and calculated by subtracting the grand mean from the column mean for each stressor), the person-by-situation interaction ($p{*}s_{ij}$, conceptually the consistent deviation between the data point and the predicted data point based on person and situation effects, across time and calculated by subtracting the row and column means from each cell and adding the grand mean), and error (ε_{ijk}, calculated as deviations not attributable to these sources):

$$X_{ijk} = c + p_i + s_j + p{*}s_{ij} + \varepsilon_{ijk} \qquad (1)$$

The variables *p, s,* and *p*s* are random variables whose variances are σ_p^2, σ_s^2, and σ^2_{p*s}, respectively. Because variance signals importance, the size of σ_p^2, σ_s^2, and σ^2_{p*s} indicates the importance of each component in explaining stress reactivity. The relative importance of each component can be quantified by dividing each variance term by the total variance. For example, the relative importance of the person perspective is σ_p^2 divided by $\sigma_p^2 + \sigma_s^2 + \sigma^2_{p*s}$. By collecting data resembling that of Table 2, I can run this model and calculate the proportion of stress reactivity attributable to each source of variance.

As with any study, the meaning of the proportions will be specific to the population of people and the population of situations from which the samples are obtained. In the studies in this dissertation, samples are obtained from person populations of 1) racially diverse college students in an introductory psychology course, and 2) geographically and age diverse U.S. adults. Across two studies that present complementary strengths and weaknesses, I provide the first answer to the question of relative importance in stress reactivity. Perhaps more importantly, I show how crossed random effect modeling provides new insight into stress theory by introducing a new way of thinking about the person versus situation debate.

Chapter 2: Statistical Analysis & Bayesian Workflow

2.1 Statistical Analysis

As described in Chapter 1, both studies were designed such that many different people responded to many different stressful situations. In Study 1, participants responded on two items at two different time points. This implies that the true data generating process for Study 1 can be represented by the following formula:

$$\text{Stress Reactivity}_{hjkl} = c + p_h + s_j + t_k + i_l + (ps)_{hj} + (pi)_{hl} + (pt)_{hk} + (st)_{jk} + (si)_{jl} + (it)_{lk} + (psi)_{hjl} + (pst)_{hjk} + (pit)_{hjl} + (sit)_{jkl} + (psit)_{hjkl} + \varepsilon_{hjkl}$$

where:
p_h = person
s_j = stressor
i_l = item
t_k = time

In Study 2, there is only one item and participants could experience the same stressor on more than one occasion. Therefore, the data generating process for Study 2 is:

$$\text{Stress Reactivity}_{hjkl} = c + p_h + s_j + t_k + (ps)_{hj} + (pt)_{hk} + (st)_{jk} + (pst)_{hjk} + e_{hjk}$$

where:
p_h = person
s_j = stressor
t_k = time

Data generated by these processes implies the possibility of estimating crossed random effect models to decompose variability in stress reactivity. In a multilevel modeling framework, stress reactivity would be regressed on a fixed intercept and random intercepts of person, stressor, time, item, the person-by-stressor interaction, and so on.

Prior scholarship in psychology that uses crossed random effect modeling, namely on the SRM, has tended to exclude the error term when interpreting results. This is because the error term has either been assumed to represent the interaction term when there is only one time point, which means the interaction term and error cannot be disaggregated (Kenny, 1994), or because the error term is thought to represent random chance deviations and psychometric error. To the first point, our study design does enable us to separate the interaction term from error, which I consider relevant since the interaction term is too important to be confounded with error. To the second point, while I think it is possible that the error term represents random chance and psychometric error to a large extent, I also believe that it contains meaningful theoretical information. Specifically, in the stress literature appraisal theory states that reactivity depends on a person's idiosyncratic interpretation of an event in the moment, an interpretation that would not necessarily replicate even for the same person in the same situation at a separate time point. This could be because of people's ephemeral moods (Charles & Almeida, 2006) and proximate life events (McEwen, 1998) or because of some other mechanism (e.g., Engel & Gunnar, 2020). Some people refer to this phenomenon as the person-by-situation interaction, although with a different meaning than that described in Chapter 1. In the vernacular of crossed random effect modeling, these types of effects would make up part of the error term. Therefore, in our results sections, I present results that both include and exclude the error term from the analysis. Excluding the error term jibes with prior work on crossed random effect modeling in psychology and most directly answers our research question posed in the Introduction. Including the error term gives us some insight into the relative importance of the combined effect of appraisals, ephemeral moods, proximate life events, psychometric error, and random chance.

I followed guidelines set forth in the Gelman et. al (2020) preprint outlining best practices for a full Bayesian workflow. I pre-registered our data analysis plan according to this Bayesian workflow, which can be found on our OSF repository (https://osf.io/qs5vu/). The

Bayesian workflow is a dynamic approach to statistical modeling, one that combines simulation, model building, and model comparison to arrive at optimal models. The Bayesian workflow seems somewhat counter to the pre-registration movement in psychology because preregistration is about proposing and testing one model while the Bayesian workflow is about continuously updating and changing a model. I believe that the merits of pre-registration can still be upheld within a Bayesian workflow, insofar as the analyst states their variables of interest a priori. P-hacking is prevented this way. Readers interested in the details of every step of my implementation of the Bayesian workflow should read the section below. There, I assume that readers are familiar with crossed random effect modeling, multilevel modeling, and Bayesian estimation.

2.2 Bayesian Workflow

As specified by Gelman et. al, (2020), a Bayesian workflow follows the flow chart depicted in Figure 2. All R code, model objects, and visualizations can be found on my OSF repository. I recommend reading the Bayesian Workflow Pre-registration and R code prior to reading this section. The pre-registration document outlines my reason for following each step that outline below, and the R code contains step-by-step commentary of the Bayesian workflow as it was conducted. Next, I outline key takeaways from this process.

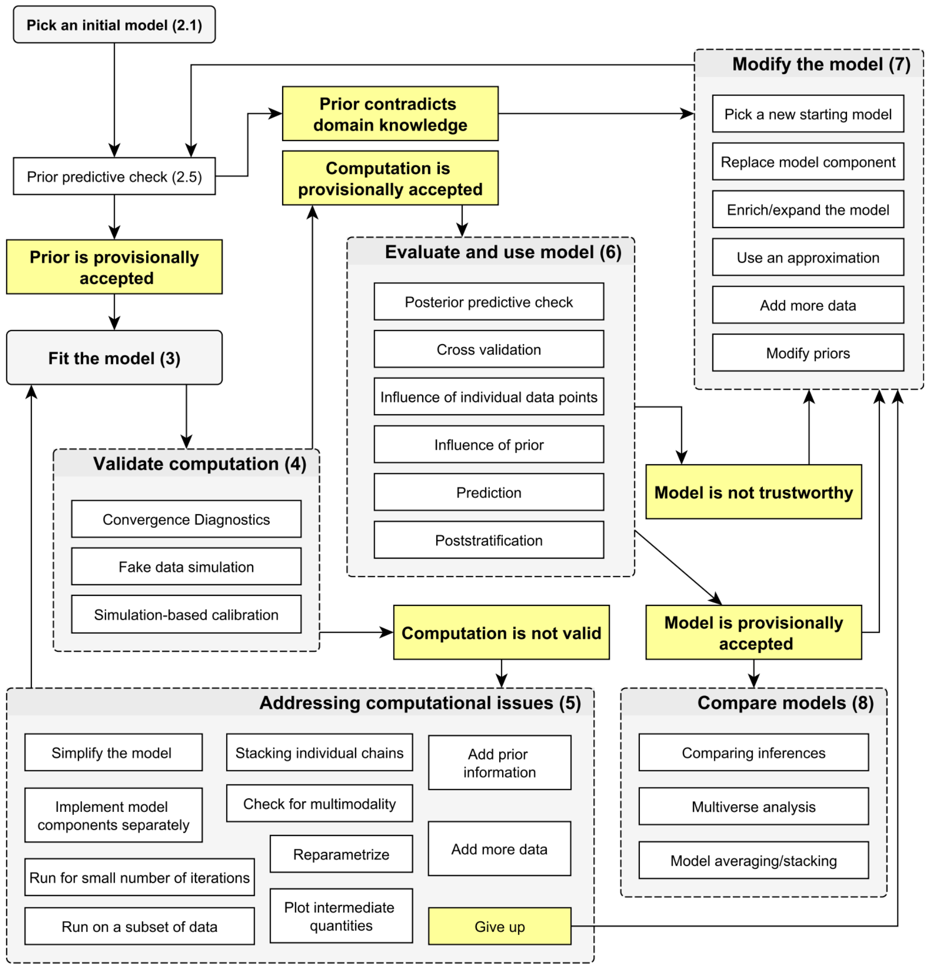

Figure 2: Gelman et. al (2020) Bayesian Workflow

The first step of the Bayesian workflow is to simulate data that resembles the hypothesized data generating process and pick an initial model by running various candidate models. Put simply, the data were fixed and the models were variable, as I tried 1) estimating more and more parameters and 2) testing different distributional assumptions in the models. I simulated a dataset according to equation 1 so that it reflected the general shape of the raw data and ran different versions of variance decomposition models to determine the best initial model on the basis of: 1) posterior predictive fit and 2) convergence. See Figures 3 and 4 for visualizations of the raw data from Study 1 and 2, respectively.

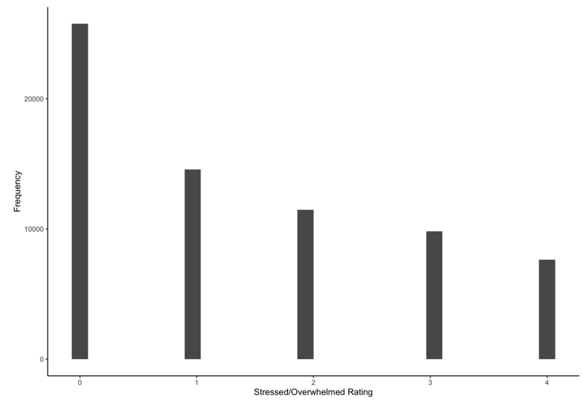

Figure 3: Raw Frequencies of Ratings on the Y Variable in Study 1, Stressed/Overwhelmed

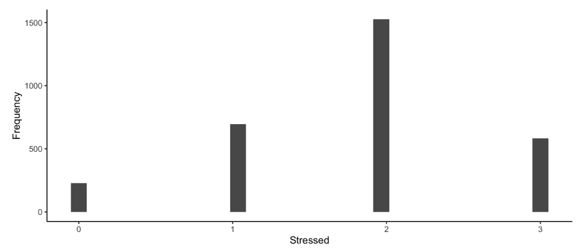

Figure 4: Raw Frequencies of Ratings on the Y Variable in Study 2, Stressful

I considered posterior predictive fit first on the basis of the likelihood distributions. Remember that for each parameter, Bayesian estimation multiplies the likelihood distributions by the prior distributions and this gives rise to posterior distributions. The likelihood distributions represent the probability of the observed data given a range of parameter values. For the random effects—the variances of person, situation, and person by situation—were limited because brms only estimates models with either a Gaussian or Student's T distributions due to the complexity of the correlation matrix that the random effects imply. Simulation showed that because the range of the outcome variable is limited between 0 and 4, normally distributed random effects were superior to Student T because the latter outputs values that far exceed the range of the scale.

For the likelihood function for the fixed effect and residual variance, I considered first the Gaussian distribution with mean *mu* and residual variance *sigma.* This model is advantageous insofar as it is the most common distribution used in psychology and in crossed random effect modeling. The downside is that the data generated by the estimated model in the posterior predictive checks exceeded the true range of Y and does not correctly identify a peak in the data when that peak is off-center, as it is in Study 1. Also, the model assumes continuous Y when it is in fact discrete in both of our studies.

Figure 5 displays the output of a model with a Gaussian likelihood and raw data that resembles that of Study 1. In this figure, the dark blue distribution represents the simulated data (i.e. the true values of Y) in a smoothed density curve. The light blue distribution represents the posterior predictive check, or the predictive values of Y based on the model in a smoothed density curve. Because the Gaussian distribution takes on only one shape, with a peak and a variance, the model has to "overshoot" and predict values below 0 in order to closely estimate the true peak of the data at 0, as seen by the light blue distribution going beyond 0 and into negative numbers. 16% of the predicted Y variables in the posterior predictive distribution were below the true range of the scale. Also, 3% of the predicted values were above the true range of the scale (i.e., above 4). Finally, notice that in attempting to keep the distribution close to the range of the scale, the model estimated the peak to be somewhere between 0 and 1, rather than at 0 itself. These issues do not emerge to this degree when the data peaks in the middle of the range of the scale, as it does in Study 2.

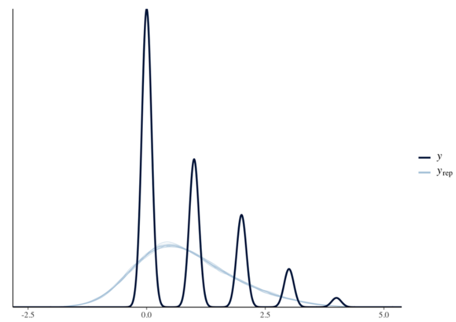

Figure 5: Posterior Predictive Check for Gaussian Likelihood on Simulated Data

Because the data peaks at zero for Study 1, I wanted to find a way to remedy the problems mentioned in the last paragraph as well as the problem that in both studies that the range of scale is constrained between 0 and 4. The Beta distribution has two parameterizations, and the intercept/phi parameterization is used in Stan (Bürkner, 2020). Readers unfamiliar with the Beta distribution can think of it here as a logistic regression with dispersion parameter phi. What is important is that the Beta distribution constrains values to be between 0 and 1. I therefore re-scaled the Y variable to be in this range. Because the Beta distribution is bounded between 0 and 1, it better represents the real data in terms of range of the scale; there is no overshooting. Moreover, Beta distributions can take on different shapes depending on their parameter values, in other words, it can have more than one peak and the peak can be at any point in the distribution.

I found that the Beta distribution could correctly identify a peak at 0. See Figure 6 for the posterior predictive check with a Beta model. However, the Beta distribution has two problems: 1) there is no way to include residual error in the variance decomposition because variance in this model represents over- or under-dispersion in a way that is fundamentally incompatible with computing total variance, and 2) our target audience is unfamiliar with Beta distributions so scientific communication becomes difficult. Therefore, I considered 2 models as candidates for the likelihood of the fixed effect and residual variance: one with a Gaussian likelihood due to its precedent in the literature and its ability to include residual error in the total variance and one with a beta likelihood due to it better fitting the data in the posterior predictive check.

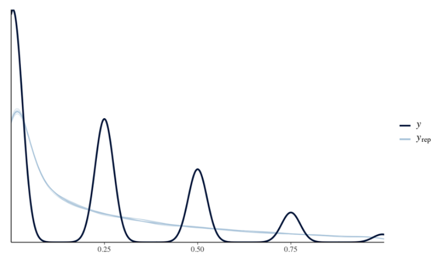

Figure 6: Posterior Predictive Check for Beta Likelihood on Simulated Data

After this step, I started to treat the data and the model as variable: I used different distributions for the variance components in simulating the dataset and tested what would and would not converge. I found that small variances cannot be estimated in the brms package in R. Taking time point as an example, in versions of the simulated data where people responded similarly on the items “stressed” and “overwhelmed”, models that estimate a random effect (i.e., variance) for item could not converge. This happened because the algorithm attempts to build the posterior distribution by finding local minima for very small steps in the posterior parameter space, and small parameter values imply flat distributions in which local minima cannot be found. Therefore, the model cannot find a reliable estimate for very small random effects. I also determined whether different models provided closer approximations to the true data generating process according to our simulation. I realized here that effects of theoretical interest (i.e., random effects of person, stressor, and person-by-stressor) were more precisely estimated when the other sources of variance (i.e. item) were included in the model. In sum, there is a balance between trying to estimate as many parameters as possible so that the parameters of theoretical interest are more precisely estimated with the fact that parameters with small variance will prevent the model from converging. In the real data, the goal becomes to try to estimate as many parameters as the model will converge on. This implied that our initial model would be one that included only the effects of theoretical interest; person, situation, and person-by-situation, and I would add random effects of item and time as possible.

Next, I treated the data as variable and the models as fixed. In other terminology, I ran simulation-based calibration to determine the extent to which the two candidate models would be sensitive to different raw data structures, as well as whether certain data structures make the models unsuitable for estimation (i.e. could not converge). In this phase, I found that the same pros and cons of the Gaussian and Beta models persisted no matter the distribution of the data itself.

The next and final simulation step was to conduct prior predictive checks for each model. Because different priors are required for the model with a Gaussian likelihood compared to the model with the Beta likelihood, I ran prior predictive checks on for both models. The major takeaway from the prior predictive checks for the normal likelihood was that prior distributions needed to be pretty narrow: large variances for the prior distributions for either candidate model led to predictions that well exceeded the range of the scale. I found that for the Beta likelihood, the priors also had to be specified quite strongly so as to maintain the shape of the true data structure, especially since the shape of the Beta distribution is highly variable as its parameter values change relative to the shape of the normal distribution at different parameter values. In choosing the prior distributions for the real data with a Beta likelihood model, I generated code that helped us find prior values that led to posterior predictive checks that represented the true data in both studies.

The final simulation I ran was a sensitivity analyses to determine whether the sample size for people and stressors in our studies were acceptable. First, I generated a population of stress reactivity scores based on Equation 2 assuming that the variances by person, stressor, and person by stressor were quite small. I then sampled between 1 and 100 stressors from the population of stressors and calculated the percent difference in size between the population stressor standard deviation and the sample stressor standard deviation. My goal was to determine whether 60 stressors was sufficient for the sample standard deviation to match the population standard deviation as I had 60 stressors in Study 1. See Figure 7. I found that the curve did asymptote before 60, such that the sample standard deviation was only off by around 5%. I did the same thing for the population and samples of people, finding that the sample standard deviation was at most 10% but more likely 5-6% off from the population standard deviation. I ran the same procedures for populations that had much larger variances by person, by stressor, by the person by stressor interaction, and error. In that sensitivity analysis, I continued to find that the person distribution of differences asymptoted at a number smaller than our sample size (reaching differences of around 17% by 180 people) and that the stressor distribution did the same, asymptoting at around 30 stressors (and reaching differences of around 18% by 60 stressors).

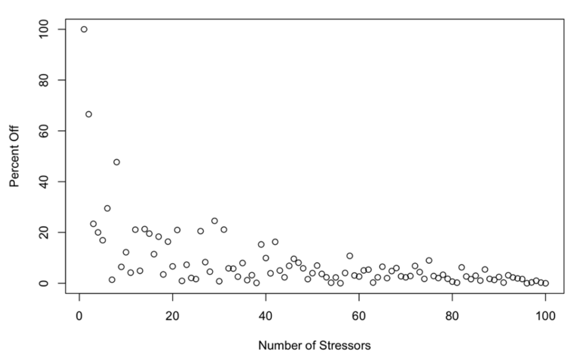

Figure 7: Example Sensitivity Analysis Visualization

Having completed these simulated data checks, my next steps were to fit the initial models to the actual data, validate that the models converged, and address any computational issues by trying different priors. Gelman et. al (2020) propose using frequentist estimation in the model fitting step to quickly determine which models fail. In Study 1, I found that a model estimating random effects of person, situation, item, time, and the person by situation interaction could converge. That meant that I tried such a model with a Gaussian and Beta likelihood on the Study 1 data. In Study 2, I found that a model with random effects of person, situation and the person by situation interaction could converge.

I then ran each of the models on both datasets a few different times, each time varying the prior distributions. In Study 1 I found, as in our simulation, that altering the priors did not change the parameter estimates or the posterior predictive check for the Gaussian models. In Study 2, I found that altering the priors had only a minor effect on the parameter estimates and no effect on the posterior predictive check. I therefore decided to use weakly informative priors for the Gaussian models, ones that made sense for the scale range based on the prior predictive check (see information in Final Model sections). I used the same priors for the data in Studies 1 and 2. For the Beta models, I determined prior distributions for the intercept and phi parameters on the basis of prior predictive checks that matched the true shape of the stress data for each study. For the Beta models in Study 1 I found that the priors did alter the parameter estimates for the fixed intercept and phi parameter, but that the priors did not alter the random effect parameters (remember that the random effect parameters are those that interest us most). For the Beta model in Study 2, I found that the priors also altered the random effect parameters.

Once arriving at a final Gaussian model for Study 1, a final Beta model for Study 1, a final Gaussian model for Study 2, and a final Beta model for Study 2, I considered whether the two Gaussian or the two Beta models were best. I wanted the model to be consistent across the studies for ease of communication. My first step was to examine the posterior predictive check both visually and analytically.

In terms of visualization, the posterior predictive checks for the final models can be seen in Figures 8-11. In Study 1, I found that the Gaussian model had the same overshooting problem as the simulated version, since the peak of the distribution is at zero. However, unlike in the simulation, with the real data the Beta model identified two peaks. Although the Beta model appropriately determined a peak at zero, it entirely missed the ordinal nature of the data because it estimated that the likelihood of the data being at .25, .5, and .75 was about equal. Moreover, the model estimated another peak at 1. Although the Gaussian model exhibits the overshooting problem, the Beta problem misclassifies the ordering of the discrete data points. In Study 2, because the data peaked in the middle of the scale, the Gaussian model makes fewer overshooting errors. The Beta model for Study 2 was severely inaccurate insofar as the peak was not even correctly identified. Based on the visualizations for these posterior predictive checks, the Gaussian model seems to be superior in both studies.

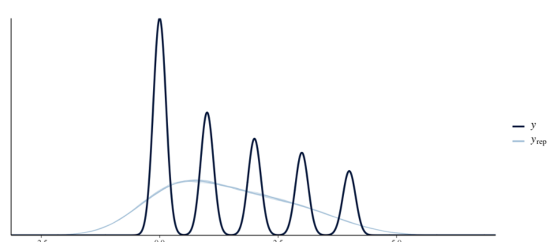

Figure 8: Posterior Predictive Check for Gaussian Likelihood: Study 1

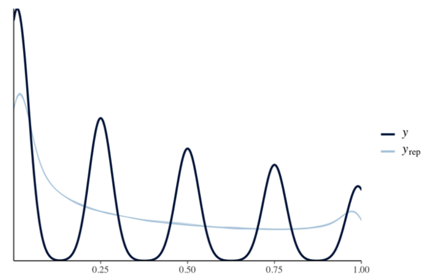

Figure 9: Posterior Predictive Check for Beta Likelihood: Study 2

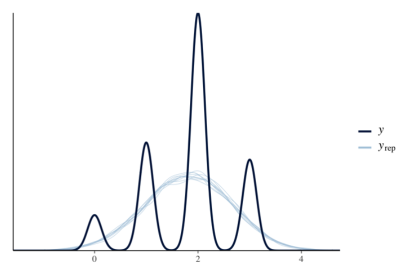

Figure 10: Posterior Predictive Check for Gaussian Likelihood: Study 2

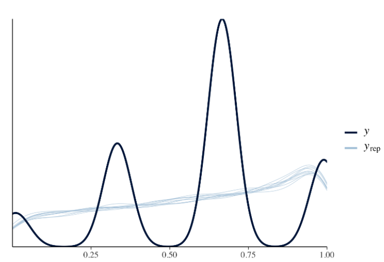

Figure 11: Posterior Predictive Check for Beta Likelihood: Study 2

Analytically, as in the simulated models, I computed the percent of the values in the posterior predictive check that were beyond the range of the scale in the positive and negative directions. I found that the Gaussian models over-shot the range of the scale, predicting 16% of the values below zero in Study 1 but only 1.6% of the values in Study 2 below zero. In terms of overshooting in the positive direction, around 4% of the values were predicted to be above 4 in

Study 1 and 7% of the values above 3 in Study 2. I also found that the Gaussian model did not pick up the peak at 0 in Study 1 but it did in Study 2. Nonetheless, the Beta models with the real data did not perform as well as they did in the simulated data and presented problems as I described above.

Therefore, I opted for the Gaussian model because it enables us to include residual error in the estimate of the total variance, and I find this parameter to be highly important theoretically. Moreover, a general audience is more familiar with Gaussian models so this choice optimizes ease of communication with our readership. The Gaussian model did a good job picking up the shape of the distribution in Study 2, and the Beta model performed poorly in Studies 1 and 2.

Before presenting the final models and results, I would like to point out that in Study 1, I kept both items (stressed and overwhelmed) in our analysis. A colleague pointed out that scores on items could be systematically correlated within session, and that this violates the assumption of non-correlated error. To deal with this potential problem, one would need to model a random effect of item by time. However, I found that models including item and an item by time interaction term would not converge. I therefore considered models for Study 1 where I subset the data to only include ‘stress’ as the outcome versus a model using data that had both stress and overwhelmed included. I found that the parameters were almost identical in both cases and present results for the dataset that included both items.

Chapter 3: Study 1

The data from Study 1 come from a 2-part vignette study in which college students imagined themselves in each of 60 stressful scenarios and indicated how stressed and overwhelmed they would be in each scenario on two separate occasions. As described below, there are several benefits to this study design.

The first is that I sample from a well-defined and relevant population: undergraduate and post-baccalaureate college students. College introduces uniquely demanding daily stressors for young adults. Around 78% of them report being moderately stressed and around 10% report being severely stressed (Piercaell & Keim, 2007; Pryor et al., 2010). The vulnerability of this population has prompted researchers to design tailored stress-reduction interventions (see, for example, Chiauzzi et al., 2008), interventions which could benefit from the insight garnered from a stress reactivity decomposition. Another benefit to sampling from college students is the diversity of the sample on several dimensions that are relevant for stress reactivity. Because variability signals importance in crossed random effect modeling, recruiting a diverse sample of people is imperative to accurately estimate the variance (importance) of person-level variables. College students are diverse, relative to the general U.S. population, in terms of racial, ethnic, and socioeconomic status since institutions of higher education make special efforts to recruit a representative sample of students (College Demographics & Diversity Report, 2022; US Census, 2020). Moreover, college students are diverse on a number of critical psychological variables relevant to stress reactivity, including neuroticism (Afshan et. al, 2015). Taken together, the fact that I sample from a population of college students implies that the importance of person-level variables will be well represented.

The vignette design of the study also offers several advantages. First, the vignettes were designed to contain only objective information and to minimize the role of subjective appraisals. In real-life scenarios, it is sometimes difficult, perhaps impossible, to disentangle the subjective from the objective when people self-report the stressful events they experienced (Hurrell et. al, 1998). In that case, person-level variance would be confounded with situation-level variance, as the scenario itself would contain subjective appraisals. Second, the vignette nature of the study enables an exact replication of the scenarios. I presented participants with the exact same stressful situations one week apart. In real life, it is almost impossible to exactly replicate a situation, meaning that variance attributed to situation would be confounded with error. Finally, the vignette design ensures that situations are constant across persons. In real life, it is difficult to find scenarios that were exactly the same for two different people. Therefore, noise would be introduced because differences between people's reactivity to a situation could be due to true differences between those people, or due to differences in the situation they are reacting to.

Finally, the combination of a defined population with the vignette design allows us to generate scenarios specific to our population. With a broad population (i.e., New York City adults, Americans 18-45, etc.), it would be difficult to design scenarios that everyone in the sample found relatable. Being unable to relate to or imagine oneself in the scenario would reduce the validity of the study. While there are certainly drawbacks to a vignette-style study, which I will discuss later, I believe that the advantages of the design considerably outweigh those limitations.

3.1 Participants

Students enrolled in the introductory psychology course at Columbia University in the Fall semester of 2020 and the Spring semester of 2021 were asked to participate in a departmental subject pool for course credit. Students were required to complete 6 subject pool credits, else complete an additional assignment. The vast majority opted to participate in studies by logging into an online portal and choosing studies on the basis of availability and credits; no information was provided about the study itself. The data for Study 1 come from students who selected to participate in our 2-part study in exchange for 3 credits. During enrollment, students selected the date and time for both sessions, which occurred on the same day and time one week apart (i.e., if a student signed up for Part 1 on a Monday at 3pm, they also signed up for Part 2 on the following Monday at 3pm). This means that many students responded to many stressful situations on two occasions, enabling the person by situation effect to be disaggregated from the error term. To ensure that there were no systematic differences between the sample populations by semester, I ran t-tests for average chronic stress (range 1–5, $M_{diff} = .01$, $p=.83$), life satisfaction (range 1–6, $M_{diff} = .03$, $p=.78$), and mood (range 1–5, $M_{diff} = .08$, $p=.42$) and found very small effect sizes and no significant results. I therefore collapsed the data across the two semesters.

The final sample consists of 368 participants. The racial/ethnic breakdown of the sample was: 37% non-Hispanic white, 25% Asian, 13% Hispanic white, 14% mixed race, 9% Black/African/African-Caribbean, and 3% other. 73% of the sample were psychology majors, 18% were undecided, and 7% were not psychology majors. In terms of gender, 60% of the sample identified as cis-female, 31% as cis-male, 2% as non-binary, and one person identified as trans-female and one person identified as trans-male. For socioeconomic status, 5% indicated they were in a lower socioeconomic category, 31% indicated middle socioeconomic status, and 63% indicated upper socioeconomic status.

On psychological measures related to stress reactivity, I found that the sample exhibited a sufficient amount of variability on all measures. In terms of the Big 5 personality traits, on a 1-7 scale (Gosling et al., 2003) participants had a mean neuroticism of 3.8 (SD=1.4, range =1-7), a mean extraversion score of 4.2 (SD=1.7, range =1-7), a mean agreeableness score of 4.9 (SD=1.2, range =1-7), a mean openness score of 5.3 (SD=1.1, range – 1.5-7), and a mean conscientiousness score of 5.3 (SD=1.3, range =1.5-7). As far as loneliness on the UCLA Loneliness scale (Russell, 1996), participants rated on average 2.2 (SD=.48, range=1.1-3.5) on a 1-4 scale (*1=never, 2=rarely, 3=sometimes, 4=always)*. In terms of life satisfaction on the Diener et al. (1995) 1-6 scale, participants were on average 4.2 (SD=1.1, range =1-6). In terms of chronic stress on the Cohen et al. (1983) Perceived Stress Scale, participants reported an average of 3.3 (SD=.53, range = 1.9-4.6) on a 1-5 scale about feeling chronically stressed in the last month (*1=never, 2=almost never, 3=sometimes, 4=fairly often, 5=very often).*

3.2 Procedures

After signing up for the study, participants received an instructional email. The email contained a link for an at-home questionnaire that was to be completed at least 24 hours in advance of the first session. The at-home questionnaire contained around 15 minutes of questions from psychological measures related to stress, as well as demographic questions. Those measures are not used in the analyses here. The email also provided a Zoom link for participants' first session and asked that they attend the session with their microphone and video on, at a desk in an isolated room, and with a reliable internet connection. Participants who did not meet these requirements were not included in the analyses.

Upon arriving at the first Zoom session, participants were greeted by a member of the study team. All team members were cis-females and kept their videos off to reduce potential effects of participant bias. The research assistant read from a script the entire time she interacted with the participant. The research assistant randomized the participant into one of ten conditions. The only difference between the conditions was the order of the stimuli. Then, participants were sent a Qualtrics link. The Qualtrics survey contained a consent form, instructions, practice materials, and study materials that aligned with the research assistant's script.

First, participants read a consent form and provided verbal and written consent to partake in the study. They were told that study is about "how people's answers to certain questionnaires relate to their perceptions of events in day-to-day life", so no deception took place. Participants then completed a 3-part short version of the Profile of Mood States (POMS, Curran et. al, 1995), one asking about feelings right now in this moment, one asking about feelings in general throughout the course of their life, and one about their feelings since the beginning of the COVID-19 pandemic. Those measures are not used in these analyses. Next, participants heard the following instructions about how the study would proceed:

> "What you will do in this study is imagine yourself in a number of different scenarios. Each time you progress to a new page, a new scenario will be written at the top. Please read the scenario silently to yourself as I read it to you out loud. For each scenario, it is important that you really **imagine** yourself in the situation, visualizing it in your mind as much as possible. Then, you will indicate how stressed and overwhelmed you would feel in each scenario.
>
> It is important that you know that all scenarios contain events that you might encounter in everyday life. I are interested in daily life experiences--but not in the context of a global pandemic. **When imagining these scenarios, please refer to how you would respond at this time, if the COVID-19 pandemic had not occurred.**
>
> Also, because I are interested in daily life experience, none of the scenarios are meant to be severely stressful or represent major life events. For example, death of a loved one is a very stressful event, but I do not include scenarios like this because they are not in the realm of everyday life experiences. This means that I would like you to consider values of '4' as being very stressed--

> relative to what you might experience in everyday life. Put another way, I want to make sure you use the full range of values on the questionnaires."

Participants then completed two practice scenarios and asked clarifying questions to the research assistant. Following this, participants proceeded to the main part of the study, in which they silently read each of 62 scenarios to themselves as the research assistant read them out loud. For each scenario, participants indicated on a 0-4 scale how stressed and overwhelmed they would be, as well as whether it was easy to imagine themselves in the scenario (yes/no). Only instances where participants rated the scenario as easy to imagine were included in analyses. Responses from the first 2 scenarios (which were identical across conditions) were excluded from analyses, as they are considered calibration scenarios that helped participants acclimate to the procedure and understand the range of the scale and the types of events they would think about (see Shrout et al., 2018). Halfway through the scenarios, i.e., after scenario 32, participants took a 2-minute break in which they sat at their desk with their video and camera on. After completing the remaining 30 scenarios, participants were provided instructions about the second part of the study.

Exactly one week later, participants re-joined the zoom link and met with the same research assistant in order to complete the same task. In Part Two, participants skipped the consent form and the practice scenarios. Otherwise, the procedures were identical to Part One. Upon completing the second part of the study, participants were debriefed, thanked for their time, and provided course credit.

The reason for having participants attend a Zoom session with a research assistant who read the scenarios out loud was to ensure high quality data. Not only did the research assistant increase participant's accountability and ensure that they at least heard every scenario in full, but also the research assistant took notes about participant engagement and study procedures. Prior research has revealed poor data quality in online surveys, especially during the COVID-19 pandemic (Pozzar et. al, 2020; Uittenhove et. al, 2022). Therefore, I only include data from participants whom the research assistant considered at least a 6 on a 1-10 scale from 1=not at all engaged, 5 = somewhat engaged, to 10=extremely engaged and at least a 6 on a separate 1-10 scale asking how well the study went (reliable internet, no interruptions, etc.) from 1=extremely poorly, 5=okay, to 10=extremely well.

Documents containing all procedural instructions, training materials, and scripts can be found on my OSF repository (https://osf.io/qs5vu/).

3.3 Scenario Generation

With the help of three research assistants, I generated the scenarios according to the Daily Inventory of Stressful Events, a full description of which can be found in its primary outcome paper (Almeida et. al, 2022). To summarize, the DISE classifies daily stressful events according to several objective measures, including severity (low to extreme), the area in life in which they occur (i.e., work, finances, physical health), and who is implicated in the situation (self, other). DISE also classifies stressful events on subjective indices such as the primary appraisal domain (i.e., how someone feels about themselves, plans for the future) and the type of threat elicited (i.e., danger, disappointment). Each of these codes was used to generate 50 scenarios, as tabulated in Table 3. Note that scenarios in the '0' category were not actually stressful even though they are conceptualized in a certain domain. For example, a scenario of 0 severity in the interpersonal tension domain would describe an event where the participant is merely with another person and no tension occurs. Ten additional scenarios were also generated that were randomly classified into each category.

Table 3: Types of Scenarios

		Objective Severity				
		No severity	Low	Medium	High	Extreme
Primary appraisal domains	Disrupting daily routine **(x2)**	Interpersonal Tension	Work/Education	Home	Finances	Discrimination
	Financial situation **(x2)**	Work/Education	Interpersonal Tension	Work/Education	Home	Finances
	Way feel about self	Home	Finances	Interpersonal Tension	Work/Education	Home
	Way others feel about you	Finances	Home	Finances	Interpersonal Tension	Work/Education
	Physical health and safety	Health/Accident	Discrimination	Miscellaneous	Health/Accident	Interpersonal Tension
	Health/well being of someone you care about (**network**)	Discrimination	Health/Accident	Discrimination	Miscellaneous	Health/Accident
	Plans for future **(x2)**	Miscellaneous	Miscellaneous	Health/Accident	Discrimination	Miscellaneous
	Disrupting daily routine **(network)**	Work/Education	Discrimination	Miscellaneous	Home	Finance
	Financial situation (**network**)	Finance	Work/Education	Home	Miscellaneous	Discrimination

Note: Color key, threat dimensions, yellow = loss, green = danger, orange = disappointment, blue = frustration, pink = opportunity

A primary goal in this study is to ensure that the scenarios are constant across people, such that variability by stressors reveals true differences in stress reactivity in a way that is not confounded with noise. In order for the scenarios to be constant across people and be realistic, the scenarios were tailored to the population from which I sampled. Because it was a student sample, an undergraduate research assistant created an initial draft for each of the scenarios that reflected their own and their friends' college lives. Those drafts were checked and coded by me. Then, two blind, trained DISE coders coded the vignettes according to the DISE scheme. Only scenarios that were coded identically across the two blind coders were included in the final set of scenarios.

A sample scenario with low severity, in the work/education area in which only the self is implicated can be found below. Note that in creating the vignette, the research assistant thought about the subjective codes (appraisal and threat domain). For the example below, the research assistant believed that the event would be in the primary appraisal domain of frustration and be in the threat dimension of lost opportunity. Because these latter two codes are subjective, I did not take notice if the intended threat dimension and primary appraisal domain were "incorrectly" coded by the blind coders because there was no correct answer.

> "On your way to class today, there was a rally happening outside that made it difficult to access campus. You are therefore about 10 minutes late as you arrive to class. The professor gives you a look as you walk in, but you quickly take your seat and the professor treats you normally throughout the rest of class."

A sample vignette with extreme objective severity, in the home area in which only the self is implicated can be found below. In creating the vignette, the research assistant thought that the primary appraisal domain would be daily routine disruption and the threat dimension would be a loss.

> "You cook all of your meals inside of your kitchen, but last night when you were making dinner, the stove didn't turn on. You called a repairman to assess the issue. Today, the repairman comes and says that your stove isn't working because of a larger structural issue. It will take a long time to order new parts, have them installed, and fix the stove before you can start using it again."

A full timeline of the brainstorming process during scenario generation, how coders were trained, and the scenarios themselves can be found on my OSF repository (https://osf.io/qs5vu/).

3.4 Statistical Model

The conclusion of our Bayesian Workflow was to use the following version of a crossed random effect model:

$$Y_{ijkh} = c + p_i + s_j + (p{*}s)_{ij} + \varepsilon_{ijkh}$$

where:
Y_{ijkh} = stress reactivity for person *i* on stressor *j* at session *k* on item *h*
p_i = person *i*
s_j = stressor *j*
ε_{ijkh} = residual for person *i* on stressor *j* at session *k* on item *h* and any higher-level interactions (i.e. item by stressor interaction effects)

and:
$Y \sim N(0, \sigma^2)$
$p \sim N(0, \sigma_p^2)$
$s \sim N(0, \sigma_s^2)$
$p{*}s \sim N(0, \sigma^2_{p*s})$
$\varepsilon \sim N(0, \sigma^2_{\varepsilon})$

The reader will notice that the error term contains residuals for both item and time point. This conceptually represents replications of stress reactivity across items and time (see Bayesian Workflow for reason behind excluding effects of item and time). The model was run with a fixed intercept with random effects of person, situation, and the person by situation interaction.

As described in our Bayesian Workflow, I chose weakly informative priors. Note that the results are identical whether weakly informative priors or non-informative priors are used. The reason I chose weakly informative priors is because it is nonsensical to use priors that simulate data that exceed the range of the Y variable in the model. Therefore, I used a gaussian prior for the intercept with mean 1.5 and standard deviation .2, a Gaussian prior for the random effects with mean 0 and standard deviation .2, and a gaussian prior for the residual, ε, with a mean 0 and a standard deviation of .5. Since the results are the same as that with noninformative priors, our results match what would be found in a Frequentist, rather than Bayesian, version of the same model.

3.5 Results

Primary Analysis

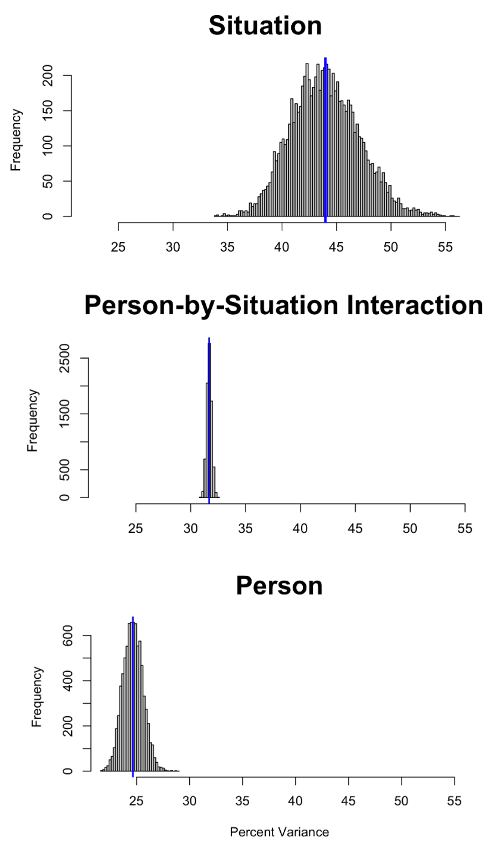

Figure 12: Posterior Probability Distributions for Study 1 Components
Note: means depicted in blue

Figure 12 visually shows the results while summaries are found in Table 2. Figure 12 shows that there was no overlap in the probability estimates, meaning we are very certain about the ordering of the importance of the components. Because Bayesian estimation was implemented, there were no single point estimates, so I used the means as summaries for the posteriors. Therefore, for the decomposition, I divided the variance attributable to each factor (the mean of the posterior distribution) by the sum of the variances for all explained factors (the means of each of the posterior distributions). For example, the percent of stress reactivity attributable to person is $\mu(\sigma_p^2)$ divided by $\mu(\sigma_p^2) + \mu(\sigma_s^2) + \mu(\sigma^2_{p*s})$. Based on the credibility intervals (computed as the 2.5th and 97.5th percentiles of the posterior distribution in the numerator divided by $\mu(\sigma_p^2) + \mu(\sigma_s^2) + \mu(\sigma^2_{p*s})$) and magnitudes of the variance components, the results suggest that all components contributed a meaningful amount of variability. The situation emerged as most important, accounting for 44% of stress reactivity (CI: 39% - 51%). Next was the person-by-situation interaction, accounting for 32% of stress reactivity (CI: 31% - 32%) followed by the person, which accounted for 24% of stress reactivity (CI: 23% - 27%). Overall, these three factors accounted for 74% of the total variability in stress reactivity.

Table 4: Study 1 Results

Component (in order)	% Variance – Explained (Primary Analysis)	% Variance - Total (Secondary Analysis)
Situation	44%	32%
Person by Situation	32%	24%
Person	24%	18%
Error	--	26%

Secondary Analyses

It is common to report results for crossed random effect models in the way I just did, where error is excluded from the denominator (Kenny 1994, 2019). The reason to exclude error from the analysis is that the meaning of the error term is vague. However, I think the error term might also be psychologically and practically interesting. Remember that the error term is the deviation between a cell value (refer to Table 2) and the model-predicted value for that cell. In concrete terms, the error term is a person's reactivity to a particular scenario that deviates from how that person usually reacts to situations in general, how stressful people generally find that situation, and how much that person specifically reacts to that kind of situation. Such a deviation could be due to psychometric error, such that the person's interpretation of the scale momentarily changes. The deviation could also be due to random chance, or the fact that a person's reactivity is not entirely deterministic (see Kenny, 1979). But that deviation could also occur because a person experienced a similar situation earlier in the day, and therefore reacts more to this scenario in this particular moment. Finally, the error term could take on other meanings beyond the ones I have theorized. Unfortunately, I cannot parse apart all the different explanations for the error term; its meaning is vague.

However, I still think it worthwhile to at least present a version of the model that includes interpreting the error term. I therefore present results when the residual variance is included in the denominator of the analysis; when determining the portion of stress reactivity attributable to the person, for example, I divided σ_p^2 by $\sigma_p^2 + \sigma_s^2 + \sigma^2_{p*s} + \sigma^2_e$. I also computed the portion of the total variability attributable to error by dividing σ_e^2 by $\sigma_p^2 + \sigma_s^2 + \sigma^2_{p*s} + \sigma^2_e$. As seen in the third column of Table 4, these computations suggest that error constitutes a meaning amount to the total variance, around 25% of it (CI: 24% - 25%).

I realized that there is one major component of the error term that I could parse out with our study design; the effect of current mood. Prior research shows that current mood shapes people's cognitive evaluations of situations (Edwards & Templeton, 2005). Therefore, beyond the person, situation, or person by situation interaction affecting stress reactivity, a person's mood might influence stress reactivity. This effect can be seen if time is included in the (session

1 or 2). If a person is in a good mood on one session day and a negative mood on the other session day, then the person would chronically react more to all stressors on the bad-mood relative to the good-mood day. This can be approximately measured by the effect of session. I quickly ran a frequentist model including session in the analysis. These results need to be interpreted with caution since two sessions are not enough to obtain a reliable estimate of time. Nonetheless, in our model suggests that session accounts for only a tiny fraction of stress reactivity, less than 1%. I hope future research will design new studies that attempt to parse out the different components of the error term.

3.6 Study 1 Discussion

Study 1 implemented a vignette design among college students to decompose variability in psychological reactivity to daily stressors. In the primary analysis, all three factors emerged as important. This implies than an either/or view on stress reactivity, in which either the person or the situation is the focal point of analysis, does not apply. Instead, both person and situation matter, as well as the person-by-situation interaction. Nonetheless, the fact that the situation emerged as the *relatively* most important, implying that regardless of who a person is, some situations are simply more stress-inducing. Perhaps psychological research should focus more reducing reactivity not just within a person, but instead removing the source itself. This implication is further substantiated by the fact that the person explained the least amount of variance. The extent to which features that are chronic to a person—their neuroticism, loneliness, social support networks—mattered less than the other types of variables. In the middle was the person-by-situation interaction. Overall, these results providing preliminary insights into the relative importance of the person, situation, and person-by-situation interaction among college students.

However, there are limitations to this study. It would be worthwhile to investigate a population other than college students, one that might imply more generalizable results. Moreover, the nature of the vignette design implies that the results may not be replicated in the context of real-life daily stressors. Finally, how stress-reactive a participant reports they would be in a certain scenario is biased by the participants wanting to maintain an image of being a level-headed, non-reactive person both to themselves and the research team. In Study 2, I address these limitations by using a sample of real-life daily stressors among a much larger and more age-diverse sample of adults in the United States; I use data from the Midlife in the United States (MIDUS) 2 study. Although the MIDUS 2 study suffers limitations that are the strength of Study 1, MIDUS 2 can provide insight into the decomposition of daily stress reactivity that Study 1 cannot.

Chapter 4: Study 2

The data from Study 2 come from the National Study of Daily Experiences (NSDE) for the second wave of the MIDUS study (see Almeida, 2005). The population was 18-85 year-old Americans living in geographically diverse parts of the country. Although the sample is predominantly white, it represents a population that is diverse in terms of psychological states, ages, lifestyles, political orientations, and socioeconomic statuses. The person variance may therefore account for a larger amount of variability, since the population includes individuals whom I expect to be very different from one another. This study will enable us to test this possibility by comparing the results to those of Study 1. Finally, sampling from a broad population has further-reaching intervention implications. If, for example, the situation again emerges as most important amongst this diverse group of people, then people could be said to react similarly to the same situations regardless of who they are.

In terms of the design, in which adults were called by a research assistant and asked to generate small vignettes of the scenarios, there are several advantages. The first is that I can be confident that stress reactivity is attributable to real-life, rather than hypothetical, scenarios. The measures for stress reactivity will be in reference to actual events that happen, and therefore contain more face validity than Study 1.

4.1 Participants

Participants were 955 U.S. adults participating in the second wave of the MIDUS study from 2004-2006 were included in analyses. These participants were also part of the National Study of Daily Experiences (NSDE), whose data were analyzed as part of the Daily Inventory of Stressful Events (DISE, Almeida et. al, 2002). On average, participants were 56 years old, but there was considerable variability by age (SD=12 years, range= 33-85 years old). The racial/ethnic breakdown of the sample was: 91% non-Hispanic white, 0.1% Asian, 2% Hispanic white, 2% Black and/or African American, and 4.9% other. In terms of gender, 58% of the sample identified as cis-female, 42% as cis-male, and participants were not given the option to indicate their sex outside of these categories. For socioeconomic status, 49% were in a lower socioeconomic category, 38% were in the middle socioeconomic status, and 13% were in the upper socioeconomic status, according to mean household income cutoffs from the Pew Research Center (2020).

On psychological measures related to stress reactivity, I found that the sample was fairly diverse in terms of the range and standard deviation of the sample relative to the range of the scales. For the Big 5 personality traits, measured according to the Big 5 factor taxonomy (John, 1990), on a 1-4 scale participants had a mean neuroticism of 2.0 (SD=.62, range =1-4), a mean extraversion score of 3.1 (SD=.56, range =1.2-4), a mean agreeableness score of 3.4 (SD=4.9, range =1.8-4), a mean openness score of 2.9 (SD=.53, range – 1.1-4), and a mean conscientiousness score of 3.4 (SD=.45, range =1-4). As far as the face-valid loneliness item in reference to the last 30 days, participants rated on average 4.4 (SD=.83, range=1-5) on a 1-5 scale measuring how often they felt lonely (*1=all the time, 2=most of the time, 3=some of the time, 4=a little of the time, 5=none of the time)*. Finally, in terms of life satisfaction on a 1-10 scale, participants were on average 7.8 (SD=1.2, range =2.7-10) on a 1-10 scale for a 5-item measure (Prenda & Lachman, 2001).

4.2 Procedures

Ten years following MIDUS I (N = 7180), participants were followed up to complete the second wave of the study, MIDUS II (*N* = 4963). MIDUS II was designed to examine age-related changes in psychological and physical health among adults in the United States. A subset of participants in MIDUS II completed an additional 8-day daily diary study, in which participants were contacted via telephone each evening for 8 consecutive days. During the phone call, participants responded ‘yes’ or ‘no’ to each of 7 stem questions, which were meant to begin a small conversation about the most likely types of stressful events that a person could experience in daily life. Specifically, they were asked:

> “1) Did you have an argument or disagreement with anyone since this time yesterday?
> 2) Since (this time/I spoke) yesterday, did anything happen that you could have argued about, but you decided to let pass in order to avoid a disagreement?
> 3) Since (this time/I spoke) yesterday, did anything happen at work or school (other than what you've already mentioned) that most people would consider stressful?
> 4) Since (this time/I spoke) yesterday, did anything happen at home (other than what you've already mentioned) that most people would consider stressful?
> 5) Many people experience discrimination on the basis of such things as race, sex, or age. Did anything like this happen to you since (this time/I spoke) yesterday?
> 6) Since (this time/I spoke) yesterday, did anything happen to a close friend or relative (other than what you've already mentioned) that turned out to be stressful for you?
> 7) Did anything else happen to you since (this time/I spoke) yesterday that most people would consider stressful?”

If a participant responded ‘yes’ to any of these stem questions, they were asked additional follow up questions so that a vignette-like description of what happened was generated. Participants did this for every stem question that they answered ‘yes’ to. Participants also answered the question, “*how stressful was this for you?”* on a scale with *0 = not at all, 1=not very, 2=somewhat, 3=very.* Further details can be found in the codebook provided on ISPCR for the NSDE II dataset.

The final dataset consists of 3034 diary days. For each person, stressor, and day in the dataset, two blind coders classified the vignette-like descriptions from the transcribed phone calls according to the Daily Inventory of Stressful Events (DISE), as briefly outlined in Study 1. Readers interested in a full description of the coding from the DISE can refer to the original publication describing it (Almeida, 2005). For our analyses, there was a trade-off in that I wanted to classify the stressors as accurately as possible but also so that there were enough replications in each cell that the crossed random effect model could be run. Therefore, I used the coder-rated objective severity of the stressors combined with their content classification. This resulted in 27 unique stressors because there were 7 stem questions times 4 severity levels minus one missing stem/severity combination (discrimination/extreme severity).

4.3 Statistical Model

I used the exact same crossed random effect model in this study as I did in Study 1:

$$Y_{ijk} = c + p_i + s_j + (p*s)_{ij} + \varepsilon_{ijk}$$

except this time:

Y_{ijkh} = stress reactivity for person *i* on stressor *j* at time *k*
p_i = person *i*
s_j = stressor *j*
ε_{ijk} = residual for person *i* on stressor *j* at session *k* and any potential higher-level interactions

and:

$Y \sim N(0, \sigma^2)$
$p \sim N(0, \sigma_p^2)$
$s \sim N(0, \sigma_s^2)$
$p*s \sim N(0, \sigma^2_{p*s})$
$\varepsilon \sim N(0, \sigma^2_\varepsilon)$

In this model, time refers to the day on which a person experienced a certain stressor. Because this was a daily diary study, replications—which are necessarily to disaggregate the p*s effect from error—consisted of the same person experiencing the same situation on at least two separate days. The model was run with a fixed intercept and random effects of person, situation, and the person by situation interaction.

As in Study, I chose weakly informative priors, the same priors that I used in Study 1. As with the previous study, the results are identical whether weakly informative priors or non-informative priors are used, but weakly informative priors are preferable because they make sense given the range of Y in the model. Concretely, I used a Gaussian prior for the intercept with mean 1.5 and standard deviation .2, a gaussian prior for the random effects with mean 0 and standard deviation .2, and a gaussian prior for the residual with a mean 0 and a standard deviation of .5. Since the results are the same as that with noninformative priors, our results match what would be found in a Frequentist, rather than Bayesian, version of the same model.

4.4 Results

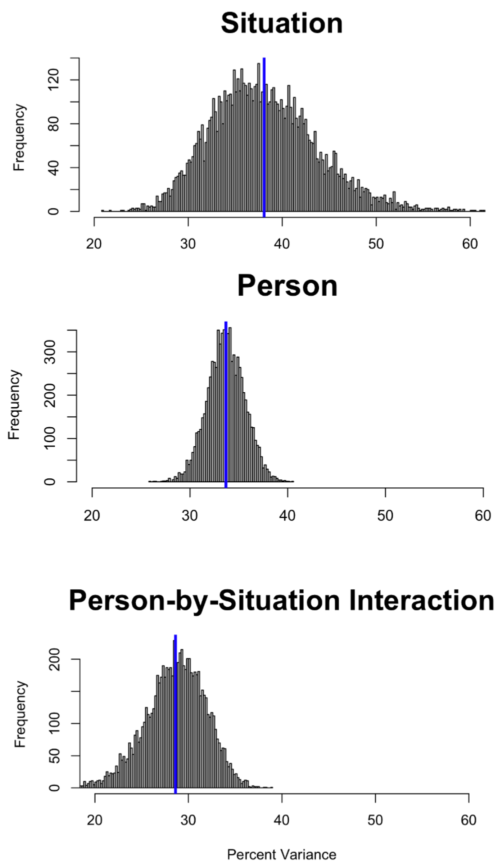

Figure 13: Posterior Probabilities Distributions of Study 2 Components
Note: The blue lines are the means of the posteriors.

The results for Study 2 are visualized in Figure 13 and are summarized in Table 5. As in Study 1, all components contributed a meaningful amount of variability. In fact, these components accounted for 66% of the total variability in stress reactivity. In relative terms, the situation emerged as most important, accounting for 38% of the total variance (CI: 28% - 51%).

Next was the person, accounting for 34% of the total variance (CI: 30% - 38%) followed by the person by situation interaction, which accounted for 30% of the total variance (CI: 22% - 34%).

Error also constituted a large part of the total variance, accounting for 35% of the total variance (CI: 33% - 37%). In our analysis of the effect of day on reactivity, our proxy for mood, I found again a very small effect, less than 1% of the total variance.

Table 5: Study 2 Results

Component	% Variance (in order) - Explained	% Variance - Total
Situation	38%	25%
Person	34%	22%
Person by Situation	30%	18%
Error	--	35%

Figure 13 displays the posterior probability distributions for the estimates of the percent reactivity attributed to each component. In this study, there is more uncertainty around the point estimates for each component, especially in the estimate for the situation. This is because there were only 8 days of the diary study and because the situations were not identical across persons. Overall, the point estimates for each component overlaps only a small amount with the distributions for the other components (i.e. the point estimate for the situation exceeds almost the entire distribution for the estimate of person and the person-by-situation interaction). Nonetheless, I are less certain than I were in Study 1 about the ordering of the importance of each component.

4.5 Study 2 Discussion

Study 2 was a daily diary study in which U.S. citizens were called each evening for 8 days and asked to describe the stressful events they experienced throughout the day. Psychological reactivity was measured as participant's self-reports on a question asking how stressful the situation was for them. The situations were classified according to the objective severity as rated by two blind coders on the DISE and the content classification of the stressor. As in Study 1, results show that all three factors emerged as important. It was not the case that the person *or* the situation *or* the person-by-situation interaction mattered, but instead that all three components explained a considerable portion of stress reactivity. In analyzing the relative importance of the three components, I found again that the situation emerged as the *relatively* most important. This means that there was considerable consensual agreement across people of diverse ages, socioeconomic statuses, personality profiles, and other psychological traits regarding the stressfulness of certain types of situations. In contrast to Study 1, the person emerged as the next important in relative terms. This is not very surprising given that the population of people from which I sampled was more heterogeneous. Finally, the person-by-situation emerged as least important in relative terms, meaning that in this population the diathesis-stress model, though important, has less empirical support than the other theoretical frameworks. Overall, these results providing preliminary evidence regarding the relative importance of the person, situation, and person-by-situation interaction for real-life daily stressors among mostly White American adults from all over the U.S.

In terms of limitations, a major drawback is that the situations were not constant across people. For example, one situation category was interpersonal conflicts at a DISE-rated level of 2. Although many people experienced this type of stressor, certainly the interpersonal conflicts themselves were different across persons. Therefore, there was additional noise in the model, exhibited in the higher relative proportion of error in the residual part of the model. Moreover, because people self-reported the situations, they could have been colored by people's subjective interpretation of the situation. It is easy to imagine that a highly reactive person might provide more detail and issues related to a stressor relative to someone who is not highly reactive. Therefore, the person and situation components of the model might be confounded in this study. Given that the DISE scheme was designed to disentangle the subjective from the objective in the situation vignettes, I expect this issue to be small but non-zero.

Chapter 5: General Discussion

I proposed a novel theoretical and empirical framework to better understand reactivity to daily stressors. I theorized that a person's reaction to any stressful situation could be explained in part by who they are (i.e. their neuroticism, their loneliness, their upbringing), in part by the situation they are in (i.e. the area of life in which it occurs, its chronicity, the amount of disruption it causes), and in part by the idiosyncratic combination of who a person is within a particular situation (i.e. diathesis-stress). Rather than debate between the primacy of the person versus the situation in stress reactivity, I argued that both could be important in addition to their interaction. Across 2 studies, I found empirical evidence for this claim; over 70% of the total variance in stress reactivity was attributable to these three components, and all three components emerged as meaningful. In relative terms, the situation emerged as most importance across the two studies, which was striking given differences in the populations of people and daily stressors from which they sampled. These findings emphasize the need for psychology to develop interventions that not only try to change aspects of who a person is, such as how mindful they are, but to also intervene on the situations themselves, perhaps by removing the frequency of stressful situations. Interestingly, the relative importance of the person and the person-by-situation factors differed between studies, which I discuss below. Finally, the error term exerted varying amounts of influence depending on the study, although a non-negligible portion of stress reactivity was left unexplained in both.

The fact that the situation emerged as most important in both studies implies that regardless of who a person is (how neurotic, lonely, or anxious they are in general), some situations are simply more stressful than others. Remember that the importance of the situation emerges from consensual (albeit subjectively unknown) agreement across people that some situations, such as finding out your bank account for your college tuition has run out, have higher mean reactivity relative to other situations, such as showing up to class 10 minutes late for reasons outside of your control. I find this interesting since the major theoretical framework for stress psychology, appraisal theory, mostly emphasizes differences between people; i.e., how two different people in the same situation can have vastly different responses (Lazarus, 2013). Instead, I found that people actually respond in surprisingly similar ways to the same situations. That is not to say that appraisal theory is incorrect; although people have the capacity to appraise the same situation in different ways, our results from Studies 1 and 2 imply that they typically do not. This finding substantiates the use of stressor checklists and objective stressor measures (e.g., Almeida, 2005; Eckenrode & Bolger, 1997), as the stressfulness of stimuli can be considered relatively constant across people. This finding is also compatible with recent shifts in stress psychology since the coronavirus pandemic emerged, and researchers have focused on the stressful nature of homeschooling for parents (Deacon et. al, 2021), working from home (Gelanti et. al, 2021), and food insecurity (Wolfson et. al, 2021).

The fact that the person-by-situation interaction was the second most important component, in relative terms, in Study 1 among a sample of undergraduate college students at a top-tier University emphasis the importance of the diathesis-stress model for this population. Diathesis-stress describes the fact that people bring unique vulnerabilities to each stressful environmental context to which they are exposed (Zuckerman, 1999). Since I categorized stressors according to content domain (see Almeida et. al, 2002), our results imply that some students are particularly vulnerable to certain kinds of stressors, for example work stressors, while other are particularly vulnerable to other kinds of stressors, for example school stressors. I find this interesting in light of diversity, equity, and inclusion conversations that now permeate college campuses (Barnett, 2020). Our findings suggest that some students may be at particular advantages, or disadvantages, depending on their psychological characteristics, life backgrounds, and current financial status. I hope that future research further investigates the relative importance of each of these sources of vulnerability. This is particularly important given that the person component explained the least amount of relative variance; it is not the case that certain kinds of students are systematically more reactive to all stressors. Rather, the student's individuality interacts with their environment to explain stress reactivity.

In the other population of people from which I sampled, U.S. adults from the MIDUS study, the relative importance of these components was reversed. In line with the person-centered approach to stress research that characterizes much of the intervention (Gamaiunova et. al, 2019; Miller & Cohen, 2001; Roberts et. al, 2015) and resilience (Herrman et. al, 2011; Tusaie & Dyer, 2004; Wu et. al, 2013) literatures, person-level variables explained the largest amount of variance behind situation-level factors. This makes sense since the population was highly heterogenous in terms of life stage, geographic region, and socioeconomic status from which I sampled, all of which have been shown to influence stress reactivity (Cohen et. al, 2006; Steptoe et. al, 2003; Tao et. al, 2020; Uchino et. al, 2005).

Currently, stress-reduction interventions variably focus on the three components I estimated in the two studies. For example, mindfulness-based interventions rely on the assumption that changing the way people perceive events can improve their reactivity to them (Crosswell et. al, 2017; Grossman et. al, 2004); the person perspective is applied here. In contrast, interventions that take people out of their stressful contexts assume the situation perspective (Cooper & Carwright, 1997; van Loon et. al, 2020), as the stressors themselves much change in order to reduce reactivity. Finally, talk therapy rests on diathesis-stress assumptions reflected in the person-by-situation component insofar as they help people understand their unique triggers and develop strategies to either avoid triggering situations or effectively deal with them (Hooley & Gotlib, 2000; Sassaroli et. al, 2021). Now that I have provided empirical evidence of the importance of all three components, the utility of these interventions are substantiated. More importantly, the findings imply that more emphasis should be put on situation-level intervention. As a field, psychology tends to emphasize the primacy of the person (Hobfoll, 2004), developing interventions focused on changing a person's psychological state rather than their built environment. However, sociologists have developed intriguing stress-reduction interventions that focus on the situations themselves. For example, one study varied the amount of natural surroundings (i.e. trees, shrubs, other vegetation) and measured cortisol, finding that participants surrounded by more nature exhibited lower levels of the stress hormone (Beil & Hanes, 2013). Perhaps psychology would benefit from creating interventions that not only alter a person's psychological reactivity to situations via intervening at the level of the person, but also create interventions that alter the situations themselves.

Beyond the models that I estimated in these two studies, the data could be used to estimate other effects. For example, a researcher might be interested in the three-way interaction between person, situation, and time. This would reveal whether a person's reaction to a particular situation differs from one time point to the next. If it did, then I might conclude that appraisals are truly ephemeral, changing from one moment to the next in a way that idiosyncratic to even the person—a person does not appraise a situation in a consistent way across time, but instead appraises the situation in a way that is specific to that instantiation of exposure. Another potentially interesting use of the model would be to estimate the random effects as heterogenous themselves. A recent extension of the SRM enables analyses to remove the assumption of homogenous error variances in a crossed random effect model (Kenny et. al, 2021). Applied to stress reactivity, an example would be that one person's stress reactivity is primarily a function of their person-level factors, while another person's stress reactivity is primarily a function of situation-level factors. Such a finding would imply that stress-reduction interventions require person-specific targets, ones that address the component of stress reactivity most important to them.

The data and models presented in this paper are not without their limitations. One of the committee members pointed out that the nature of the study design assumes that stressful situation and stress reactivity are separable, which is inherent to the person versus situation debate. There is a circularity in the methodology and theory. More specifically, some appraisal theorists consider the separation impossible (e.g., Lazarus, 1985), meaning that the stimuli in Study 1 lack face validity. In my view, the stimuli in Study 1 are valid because participants were free to appraise the descriptions of stressful events as they please, including indicating that they are simply not stressful. Another design limitation, specifically for Study 2, is that the separation between objective and subjective stress in the simly might *not* occur. In that study, participants described the stressful events they experienced that day, which were transcribed into vignettes and coded according to an objective coding scheme, the DISE. Despite the coding scheme, appraisals were invariably present in the description of the stressful events, which means that there was more noise in Study 2. Beyond design limitations, the studies were restricted to psychological reactivity to daily stressors. Future research could expand the measure of reactivity and the types of situations to which people are exposed. For example, participants could be asked to arrive at a lab and be exposed to 3 mild, acute stressors while their physiological reactivity is measured. Finally, the research is limited by the range of the scale of the measures of stress reactivity. For practical reasons, I opted to use a 4-point measure of psychological stress. However, our Bayesian workflow revealed some instability in the models due to the restricted range of the y variable. In a replication study, it would be beneficial to see a wider and more continuous psychological reactivity scale, for example one that ranges from 0 to 100 on a slider scale.

Conclusion

In this dissertation, I proposed that reactivity to daily stressors can be decomposed into three primary components: the person, the situation, and the person-by-situation interaction. Doing so introduced a new way of thinking about the person versus situation debate in stress psychology, one that acknowledges the importance of multiple sources of influence rather than just one. Across two studies, results show that all three components matter, implying that stress reactivity is a function of who a person is, the situation they are in, and the idiosyncratic interaction between who they are the situation they are in. At the same time, the situation explained the largest amount of stress reactivity. These results emphasize the importance of interventions that not only target psychological factors, such as mindfulness, but also situational factors, such as exposure. Finally, results showed that some amount of stress reactivity is not explained by any of these components, and that stress researchers should develop new theories to explain that residual variance. Overall, this dissertation pushed forward the field of stress psychology by introducing a new theoretical and empirical model to resolve prior discrepancies in the literature, specifically by proposing a new way to resolve the person versus situation debate: rather than ask “which matters more?”, I asked “what is the relative importance of person, situation, and their interaction?”

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