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Typologies of coping in young adults in the context of the COVID-19 pandemic

Aya Shigeto^a , Daniel J. Laxman^b , Justin F. Landy^a , and Lawrence M. Scheier^c 

^aNova Southeastern University; ^bArizona State University; ^cLARS Research Institute, Inc.

ABSTRACT

The COVID-19 pandemic has created major upheavals in the lives of people worldwide. The virus has mostly affected elderly populations, but there may be corollary effects on young adults' psychosocial adjustment due to educational, economic, and occupational disruptions. Using latent class analysis, we examined unique typologies of coping in response to the pandemic among young adults. We used an expanded set of indicators including traditional measures of problem- and emotion-focused coping as well as measures of resilience and coping flexibility. We also examined whether class membership could be predicted by demographics, stress appraisal, and psychosocial characteristics including catastrophic thinking and impulsivity. The sample of 1,391 young adults (ages 18–35) was recruited via Amazon's Mechanical Turk (MTurk) and snowball methods from late-April to early-May 2020. Six classes were identified: (1) Resilient Flexible Problem-Focused Copers, (2) Resilient Inflexible Problem-Focused Copers, (3) Non-Resilient Flexible Problem-Focused Venters, (4) Non-Resilient Flexible Problem-Focused Copers, (5) Non-Resilient Flexible Non-Copers, and (6) Non-Resilient Inflexible Non-Copers. Using Class 1 as the reference class, we found perceived centrality and uncontrollability of the pandemic as well as catastrophic thinking and impulsivity were significant predictors of class membership. The mean levels of stress appraisal and psychosocial characteristics varied significantly between the classes, reinforcing the structural validity of these classes. The findings suggest the importance of training young adults to develop resilience and flexibility as well as specific coping skills that can help offset the psychological effects of dramatic lifestyle changes that may result from pandemics or other health crises in the future.

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The coronavirus disease 2019 (COVID-19), which is caused by the novel Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), reached pandemic proportions in early March 2020 (World Health

CONTACT Aya Shigeto  as1959@nova.edu  Department of Psychology and Neuroscience, College of Psychology, Nova Southeastern University, 3301 College Avenue, Fort Lauderdale, FL 33314, USA.

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Organization, 2020). As of late-November 2020, the virus has infected over 58 million people worldwide with over 1 million deaths recorded. In the United States (U.S.), the Center for Disease Control and Prevention (CDC) reported as of late-November 2020 that over 250,000 people have lost their lives to COVID-19, with over 12 million cases recorded (Center for Disease Control and Prevention (CDC), 2020).

While the pandemic has caused a disproportionate loss of life and adverse health outcomes among older adults (Perrotta et al., 2020) and those with underlying disease comorbidities (Emani, Javanmardi, Pirbonyeh, & Akbari, 2020), its disruption in social, educational, and economic activity has also increased the risk of psychological maladjustment in young adults (Yang, Tu, & Dai, 2020). Indeed, recent studies have demonstrated increased levels of emotional distress during the COVID-19 pandemic among young adults (Liang et al., 2020; Liu, Zhang, Wong, Hyun, & Hahm, 2020; Shanahan et al., 2020; Tee et al., 2020; Wang et al., 2020a, 2020b). In normal times, young adults embark on a new phase in their lives and make numerous self-defining choices with long-term consequences (Arnett, 2015; Leipold, Munz, & Michéle-Malkowsky, 2019), such as preparing for the school-to-work transition (Blustein, Juntunen, & Worthington, 2000) and establishing individuality and financial independence (Shulman, Feldman, Blatt, Cohen, & Mahler, 2005). Given these unique developmental challenges, we conducted the present study to better understand unique ways in which young adults psychosocially react to and cope with pandemic-related stressors. This inquiry will offer a valuable opportunity to develop richer insight into what resources are needed to mitigate the psychological effects that future health crises may incur on young adults.

The transactional theory of stress and coping

Historically, Lazarus and Folkman (1984) transactional theory of stress and coping has been the most widely used theoretical framework to account for the diverse ways in which people cope with stressful events. The theory suggests that people encounter and respond to distressing situations through continual interactions with their environment. When faced with a stressor, individuals will engage in a form of primary appraisal, evaluating whether the stressor is a threat that will affect their well-being and have long-term, potentially damaging, consequences. If the stressor is determined to be threatening and impactful, individuals will perform a secondary appraisal whereby they determine whether they have sufficient cognitive and social resources available to counter the threat and, if so, formulate a response that can minimize the threat. Once a person invokes the two

cognitive appraisal mechanisms and decides to address specific demands of the stressor, they activate a coping response to reduce the threat and restore homeostasis (i.e. a steady state of physiological, physical, and emotional functioning) disrupted by the stressor.

The different coping strategies that individuals can employ as they transact with the environment can be theoretically divided between problem-focused and emotion-focused coping (Carver, Scheier, & Weintraub, 1989; Folkman & Moskowitz, 2004). Problem-focused coping involves active, instrumental strategies whereby the individual thinks about how to handle a stressor, decides on a plan of action, collects necessary resources, and takes steps to ameliorate the effects of the stressor. Emotion-focused coping, on the other hand, is more reactive and aims to mitigate the negative emotional state caused by the stressor by, for example, venting (e.g. expressing intense emotions or voicing one's feelings), instead of directly dealing with the stressor itself.

Past research suggested that problem-focused coping is adaptive, while emotion-focused coping is not (Folkman & Moskowitz, 2004). However, some researchers suggest that both strategies can be considered appropriate, depending on the circumstances (e.g. Aldwin & Revenson, 1987; Folkman & Moskowitz, 2004). For example, when sources of stress cannot be controlled, problem-focused coping may be ineffective, and engaging in emotion-focused coping to tolerate, minimize, ignore, or vent may be an appropriate response. Problem-focused coping, on the other hand, may be more effective at mitigating the stress caused by controllable stressors (Lazarus & Folkman, 1987). However, there is some evidence suggesting that young adults may not necessarily expect that problem-focused coping is maladaptive for uncontrollable stressors (Conway & Terry, 1992). In addition, perceiving a stressor to be controllable can lower stress levels, even if, in reality, there is nothing a person can do to control it (Thompson, 1981). In other words, *perceiving* controllability can mitigate stress, whatever the reality of the situation may be.

Coping flexibility and resilience

Folkman and Lazarus (1980; Lazarus & Folkman, 1984) reinforced that a crucial component to the transactional model is the ability of the individual to adapt to changing circumstances and employ a variety of coping strategies as the situation requires, suggesting that flexibility is essential for effective coping (Lester, Smart, & Baum, 1994). In many respects, the “transactional” component of their model reflects the dynamic interplay between coping strategies and situational demands created by the stressor to reduce threat and maintain equilibrium (Brough, O'Driscoll, & Kalliath,

2005). Coping flexibility can be of paramount importance particularly when individuals are faced with an unfamiliar stressor (like the pandemic) because it is difficult to determine what coping strategy will be effective. Further, coping is likely not a “one-shot selection process” (Boekaerts, 2010). Flexible copers are likely to implement more than one set of coping responses, quickly gauge the success of the different strategies, and move to a different response if the first one does not fare well (Bonanno, Papa, Lalande, Westphal, & Coifman, 2004; Bonanno & Burton, 2013; Cheng, 2003; Kato, 2012). Indeed, using meta-analysis, Cheng, Lau, and Chan (2014) demonstrated the benefits of coping flexibility for psychological adjustment. Maintaining such flexibility and the ability to see problems from many different angles may be a critical component of coping responses during the pandemic.

Resilience is also an adaptive process that links individual resources with events that transpire in the external world. Resilient individuals can “bounce back” from adversity (Luthar, Cicchetti, & Becker, 2000; Rutter, 1993) and restore homeostasis as they effectively minimize stress. Resilient individuals also learn from their coping experiences, both when their coping is effective and nets favorable outcomes and when it fails to yield desired outcomes (Folkman & Moskowitz, 2004). Resilience allows individuals to persevere, creating a change in the environment to mitigate the threat and obtain the desired outcome. This is particularly noteworthy in the pandemic crisis, where resilience can influence how an individual responds to social, educational, and economic disruptions caused by the pandemic (Chen & Bonanno, 2020). Being resilient is also important for young adults transitioning to adulthood because it is a period in life replete with stressors and contains a good deal of uncertainty.

Typologies of coping

There is a considerable debate over whether individuals differ qualitatively rather than quantitatively in how they cope (Folkman & Lazarus, 1980; Louvet, Gaudreau, Menaut, Genty, & Deneuve, 2007). Qualitative differences in how people cope suggest that individuals differ in the compilation of strategies they utilize and can be classified by their particular “coping styles.” Folkman and Lazarus (1980) suggested that it made intuitive sense to expect different coping styles; however, very limited research to date has pursued this idea empirically.

Several methodological hurdles may have prevented confirmation of coping styles. First, empirical studies of coping styles have primarily used variable-centered approaches, emphasizing individual differences in terms of deviations from the mean. This approach, primarily relying on correlational

evidence, assumes that a single model parameter (i.e. regression coefficient) holds for the entire population. Minimizing the sums of squares to detect the best-fitting regression line coupled with the assumption that *one-size-fits-all* misses the opportunity to detect subtle, if not unique, differences in behavior that reflect qualities of the person rather than the variables themselves (Bogat, Levendosky, & von Eye, 2005).

A second methodological limitation is that many researchers assume that it is externally valid to empirically derive coping styles using distribution-based cut-points, dividing samples into “high” versus “low” coping individuals (Biggs, Brough, & Drummond, 2017; Brough et al., 2005; Skinner, Edge, Altman, & Sherwood, 2003). The possibility that individuals might mix and match coping styles to mitigate their stress is not a hallmark feature of these studies, lessening the likelihood of uncovering discrete coping styles that are externally valid. The use of dichotomized composite scores to contrast coping styles also assumes equipotentiality of the individual items, making it hard to discern whether an individual might emphasize one coping response over another depending on the context and the success of implementing that strategy.

One solution to these concerns is the use of a person-centered approach, which suggests that individuals cluster into qualitatively distinct subgroups that represent distinct configurations of coping skills or other psychological constructs (Bergman & Magnusson, 1997; Lubke & Muthén, 2005). In the context of coping, members of one subgroup would endorse a unique set of items representing a pattern of coping strategies that is distinctly different from members of another subgroup. In the simplest case of two coping items, each one coded Y/N, there are 2^2 or 4 discrete patterns (YY, YN, NY, and NN). A larger set of observed indicators (2^n) requires greater computational effort, and assignment to unique classes is probabilistic (Collins & Lanza, 2010). Expanding the set of indicators to involve more coping strategies creates the potential for more classes that are qualitatively, rather than only quantitatively, different.

There is now growing evidence supporting the use of classification or cluster-based techniques to empirically confirm unique coping styles. The different approaches have included *k*-means clustering (Luyckx, Vanhalst, Seiffge-Krenke, & Weets, 2010; Ohannessian et al., 2010), latent profile analysis (Aldridge & Roesch, 2008; Cavanaugh et al., 2017), and latent class analysis (Lin & Wu, 2014; Yuan et al., 2020). In their study of informal caregivers taking care of family members with dementia in Singapore, Yuan et al. (2020) identified three coping typologies based on Carver’s (1997) Brief COPE items (i.e. high use variegated strategies, medium use, low use coping). Similarly, Lin and Wu (2014) used latent class analysis with adult caregivers of frail older adults and identified three coping

typologies including one undifferentiated type with an exceptionally low endorsement of any strategy, one primarily emotion-focused, and a hybrid class balancing problem- and emotion-focused coping strategies. Notably, across these different studies, many different class structures have been extracted, which may be a function of the different assessment procedures and composition of the samples, which varied considerably.

Focus of the present study

Based on the conceptual and methodological concerns outlined above, we sought to extend prior studies of coping in three distinct ways. First, we used a person-centered approach (i.e. latent class analysis, or LCA) to derive mutually exclusive typologies of coping among young adults (ages 18–35) during the initial stages of the pandemic. This is in direct response to the claim that “coping styles” are expected to exist (Folkman & Lazarus, 1980). Second, we also expanded the conceptualization of coping beyond the traditional measures of problem- and emotion-focused coping by including indicators of coping flexibility and resilience, both of which represent distinct coping strategies that may be critically important to young adults during the pandemic. Third, we also predicted class membership from demographics, stress appraisal, and psychosocial characteristics. Demographic characteristics reflect socioeconomic factors that can influence stress and coping and also pandemic-specific responses (e.g. Nicola et al., 2020). Given the emphasis on stress appraisal in the theoretical framework posed by Lazarus and Folkman (1984), we also modeled whether the stressor is perceived to be impactful (i.e. centrality), to be under the person’s control (i.e. uncontrollability), and to have the potential to undermine one’s well-being (i.e. threat). We also included two measures of psychosocial characteristics (i.e. catastrophic thinking, impulsivity) as additional markers to validate characteristic features associated with class membership. We included catastrophic thinking because it is associated with maladaptive coping and serious psychological dysfunction in response to major stressors (Martin & Dahlen, 2005; Seligman et al., 2019). Similarly, impulsivity was considered as a valid marker because it is associated with lack of problem-solving skills (Sylvain, Ladouceur, & Boisvert, 1997) and maladaptive coping behaviors (Lightsey & Hulsey, 2002; Nower, Derevensky, & Gupta, 2004). In addition, impulsive behaviors, such as leaving quarantine, attending large gatherings, and not wearing a mask are clearly maladaptive during a pandemic.

Method

Recruitment procedures

We recruited participants through two procedures: (1) a labor market platform called Amazon Mechanical Turk (MTurk) and (2) snowball methods through universities and colleagues.¹ When potential participants were recruited using snowball methods, they were explicitly informed that they needed to be 18–35 years old and were given a direct link to the Qualtrics survey platform. These individuals did not receive any form of compensation. For those accessing the survey using the MTurk platform, potential participants (U.S. residents) initially completed a screening survey assessing eligibility (i.e. ages 18–35). The title of the screener was “Screening Survey for a Psychological Study That Pays \$1.00.” The screener contained four questions, one asking their age and three filler questions. All individuals who completed the screener were given a random string of six digits to receive compensation at the conclusion of the survey. Eligible participants—those who indicated being 18–35 years old on the screening survey—were then granted access to the main survey titled “Experiences During the Pandemic.” Both the screening survey and the main survey were conducted on the Qualtrics survey platform. The project was approved by the University Institutional Review Board (IRB) at the first author’s institution.

Participants

A total of 1,509 individuals in the appropriate age range visited the main survey on Qualtrics (either through MTurk or snowball methods), 1,185 of whom (78.53%) visited (but did not necessarily complete) the survey through MTurk.² Of those visiting the Qualtrics survey, 87 respondents (5.77%) failed either one or both attention checks (one was placed somewhere in the middle of the survey and the other toward the end), and 31 (2.05%) visited the survey but did not answer any of the 22 latent class indicators (i.e. measures of problem-focused coping, emotion-focused coping, coping flexibility, and coping resilience), leaving the remaining 1,391 as the final analysis sample. Inclusion criteria for subsequent analyses required that respondents passed both attention checks, which are instructed-response items (e.g. “If you are paying careful attention to the questions in this study, please select ‘somewhat disagree’ below”). This approach is a standard practice for data quality management (Berinsky, Margolis, & Sances, 2014) and has been shown not to compromise scale validity (Kung, Kwok, & Brown, 2018).

The mean age of the sample was 26.56 ($SD = 4.79$), and the median age was 27.00. There were slightly more females than males (60.82% female), and 33.93% of the participants were college students. Nearly 40% were single (never married) (39.76%), while about half were either in a non-marital committed relationship (24.66%) or married (25.74%). Most of the sample was White/European American (64.27%) with the remainder consisting of 13.37% Asian, 7.19% Latino/a/x/Hispanic, 7.12% multiple racial/ethnic identifies, 6.76% Black/African American, 0.50% American Indian or Alaska Native, and 0.79% other races/ethnicity. Over three-quarters of the participants (77.43%) reported that they held a job before the pandemic, while 20.78% of them lost a job because of the pandemic. Over three-quarters (79.44%) reported that they lived with their family, 7.48% lived with a roommate(s), and the remaining 13.08% lived alone. Nearly half of the sample reported that they had at least a college degree; 33.64% had an undergraduate degree, and 13.37% had a graduate degree.

Survey procedure

Data collection lasted for 2 weeks, commencing on Tuesday, 14 April 2020 (when much of the U.S. was under stay-at-home orders) and ending on Tuesday, 5 May 2020 (when many states started to consider reopening their economies). Prior to accessing the survey, respondents were presented with an electronic consent form, which informed them that the survey was voluntary and anonymous. The survey began with several demographic questions. Participants who indicated that they were currently attending college as undergraduate or graduate students were asked nine additional school-related questions such as the number of classes they were taking before and after school closure, whether their classes moved online, and whether their living arrangement had changed due to the pandemic. After answering the demographic (and school-related) questions, participants were then assigned randomly to one of three survey forms using a three-form planned missingness design (Little & Rhemtulla, 2013). This design separates the questions into three sets, A, B, and C, with each participant only viewing questions contained in two of the three sets (e.g. one participant would answer the questions in sets A and B, while another participant would answer the questions in sets A and C). Thus, every participant was presented with only a subset of the questions comprising each scale. All demographic items were present in all three forms. This design is meant to conserve time and avoid response fatigue. Using this design, every participant responded to either 71 or 73 items (an odd number of items for some scales creates this slight difference) including the demographics (and

school-related questions for those attending college) and two attention checks.

Measures

Indicators for latent classes

The survey included 22 indicators of latent class membership assessing the use of problem-focused coping, emotion-focused coping, coping flexibility, and resilience. For the LCA, we dichotomized the categorical-ordinal scales by assigning “0” to the 1–3 scale points and “1” to the 4–5 scale points. Although there are methodological drawbacks to dichotomization (e.g. DeCoster, Iselin, & Gallucci, 2009; MacCallum, Zhang, Preacher, & Rucker, 2002), the most prominent one is loss of variance, which biases parameter estimates and reduces statistical power (Cohen, 1983). This downward bias affects variable-centered analyses where dispersion is used to characterize sample behavior. In a person-centered strategy, however, the emphasis is not on dispersion or other aggregate distributional qualities (i.e. moments) that profile the sample behavior, but on unique and discrete patterns that markedly distinguish subgroup behaviors. Therefore, the repercussions are less severe when items are truncated into “yes, I used this coping strategy” versus “no, I did not use this coping strategy.”

Problem-focused coping. Seven items from the Coping Assessment Battery (Bugen & Hawkins, 1981; Spitzhoff, Ramirez, & Wills, 1982; Wills, 1985) assessed problem-focused coping. These items assess different forms of decision-making including information gathering (e.g. “Think about what information is necessary for dealing with the problem”) and weighing options (e.g. “Think about which of the alternatives is best”). All items were rated on a 5-point scale (1=Never; 2=Rarely; 3=Sometimes; 4=Often; 5=Almost always/always).

Emotion-focused coping

Four items from one of the COPE subscales assessed emotion-focused coping (Carver et al., 1989). The items tap into how people focus on and vent their emotions (e.g. “I get upset and let my emotions out”) and manage distress (e.g. “I feel a lot of emotional distress and I find myself expressing those feelings a lot”). All items were rated on the same 5-point scale used for problem-focused coping.

Coping flexibility

Five items were taken from the “adaptive coping” subscale of the Coping Flexibility Scale (Kato, 2012) to assess flexibility when coping with stress

(e.g. “When a stressful situation has not improved, I try to think of other ways to cope with it”). We did not use the other subscale (i.e. evaluation coping) as it captures individuals’ awareness of alternatives and effectiveness of current attempts to cope, which may or may not lead to an active shift from one strategy to another. All items were rated using a 5-point scale (1=Strongly disagree; 2=Disagree; 3=Neither agree nor disagree; 4=Agree; 5=Strongly agree).

Resilience

Six items were taken from the Brief Resilience Scale (Smith et al., 2008) to assess resilience—the ability to bounce back after setbacks (e.g. “I tend to bounce back quickly after hard times.” “It is hard for me to snap back when something bad happens.” [reverse-scored]). All six items were rated on the same 5-point scale as coping flexibility.

Covariates and external markers

Demographics

We considered the following demographic variables as covariates: age (continuous); gender (female = 0; male = 1); race (non-White, including Latino/Latina/Latinx)=0; White = 1); job loss (not employed before the pandemic or did not lose a job due to the pandemic = 0; lost a job due to the pandemic = 1); residential status—with family (living alone or with non-family roommates = 0, living with family = 1); residential status—with a roommate(s) (living alone or with family = 0, living with a non-family roommate(s)=1); education—earned degree [being in college or having limited or no postsecondary education (i.e. no high school diploma/GED, high school diploma/GED, vocational schooling, or some college)] = 0, having a postsecondary degree = 1); and education—some schooling (being in college or having a postsecondary degree = 0, having limited or no postsecondary education = 1). For residential status, the reference group for the two residential status dummy indicators is respondents who lived alone. For education, the reference group for the two education dummy indicators is respondents who are currently attending college as undergraduate or graduate students.

Stress appraisal

We assessed stress appraisal using three of the six subscales of the Stress Appraisal Measure (Peacock & Wong, 1990): centrality, uncontrollability, and threat. We specifically chose these three subscales as they are designed to capture primary appraisal (i.e. perceptions of a stressor), as opposed to

secondary appraisal (i.e. evaluation of personal and interpersonal resources to handle a stressor and anticipated positive outcomes of coping). A total of 12 items (four items averaged for each continuous subscale) were modified to be specific to the pandemic (e.g. “Please rate the statements below while thinking about the pandemic and the crisis that we are facing right now”). This slight modification better reflects Lazarus and Folkman (1984) position that coping is a situation-specific process and can change depending on how a stressor is perceived (i.e. primary appraisal). *Centrality* captures the extent to which the stressor has grave consequences for the self (e.g. “This situation has serious implications for me.” “I will be affected by the outcome of this situation.”). *Uncontrollability* assesses the uncontrollable nature of the stressor (e.g. “It is beyond anyone’s power to do anything about this situation.” “This is a totally hopeless situation.”). *Threat* assesses the potential damage of the stressor to one’s well-being (e.g. “This situation makes me feel anxious.” “This situation is threatening.”). All 12 items were rated on a 5-point scale (1=*Not at all*; 2=*Slightly*; 3=*Moderately*; 4=*Considerably*; 5=*Extremely*). Internal consistencies of all subscales were computed using McDonald’s (1999) Omega, and they were adequate: $\omega = 0.86$ for centrality, $\omega = 0.71$ for uncontrollability, and $\omega = 0.74$ for threat.

Catastrophic thinking

Seven items assessing catastrophic thinking were distilled from the Attributional Style Questionnaire (Peterson et al., 1982), a self-report instrument that assesses an explanatory style based on the theory of learned helplessness (Abramson, Seligman, & Teasdale, 1978). Extensive psychometric work with these items has been performed as part of the U.S. Army Comprehensive Soldier Fitness Program (Cornum, Matthews, & Seligman, 2011), as they are part of the Global Assessment Tool (GAT), an instrument used to monitor soldier resilience (Peterson, Park, & Castro, 2011). Seligman et al. (2019), also using an Army sample, reported $\alpha = 0.87$ for the same seven items in a longitudinal study linking catastrophic thinking with PTSD. In the current study, catastrophic thinking reflects a proclivity to fear the worst outcomes and make negative attributions to events in the world (e.g. “When bad things happen to me, I expect more bad things to happen.” “I respond to stress by making things worse than they are.”). The seven items were rated on a 5-point scale (1=*Does not describe me*; 2=*Describes me slightly well*; 3=*Describes me moderately well*; 4=*Describes me very well*; 5=*Describes me extremely well*). The average of the ratings was used to form a composite to capture the level of catastrophic thinking. Internal consistency based on Omega was 0.84.

Impulsivity

Seven items from the Barratt Impulsiveness Scale (Patton, Stanford, & Barratt, 1995) were used to assess motor impulsivity and disinhibition. This questionnaire yields three subscales of impulsivity (i.e. attentional, motor, non-planning), but we specifically chose motor impulsivity as it represents one's behavioral tendency to do things without thinking of consequences, and it bears conceptual and practical relevance for pandemic-related behaviors (e.g. going out, not wearing a mask, making rash decisions). Sample items include "I do things without thinking" and "I act on the spur of the moment" rated on a 5-point scale (1=Never; 2=Rarely; 3=Sometimes; 4=Often; 5=Almost always/always). One item (i.e. "I am happy-go-lucky") was dropped in subsequent analyses as it did not capture motor impulsivity and also contributed to lower reliability. The average of the ratings of the six items was used to form a composite to measure the level of impulsivity. Internal consistency based on Omega was 0.72.

Missing data treatment

Missing data estimation for the three-form planned missingness design was handled using R version 4.0.0 (R Core Team, 2018) and RStudio version 1.3.1073 (RStudio Team, 2018) with the R-package Multiple Imputation by Chained Equations (MICE) procedure (van Buuren & Groothuis-Oudshoorn, 2011). We used predictive mean matching (PMM) for continuous measures (Little, 1988), multinomial logistic regression (MLR) (polyreg) for categorical measures with more than two categories, and logistic regression (logreg) for nominal measures. Predictive mean matching is a semi-parametric imputation method, also called a fully conditional specification approach that works well with large numbers of predictors and moderate to large sample sizes (van Buuren, Brand, Groothuis-Oudshoorn, & Rubin, 2006). The method identifies the "nearest-neighbor donor" with expected values of the missing data conditioned on the observed covariates. The imputation follows Bayesian linear regression principles by iteratively drawing plausible values from the posterior predictive distribution specified by the model and replacing missing values with valid values until proper convergence is obtained (i.e. minimizing a discrepancy function through a Gibbs sampling algorithm). This procedure starts with the variable that has the least missing data, and it proceeds one variable at a time and cyclically until all variables have no missing data, thus giving it the name "chained equations." The plausibility of an imputed value is based on the closeness of means between the observed (donor case) and missing values (fitted case). This procedure has been shown, with both Monte Carlo simulation and real data, to produce efficient parameter estimates and unbiased standard errors under various distributional assumptions (e.g. deviations from

normality, heteroscedastic residuals) including continuous and categorical data (e.g. Kleinke, 2017; Vink, Frank, Pannekoek, & van Buuren, 2014) and with small samples.

We created 20 imputed data sets and conducted all subsequent complete-data analyses using the Mplus statistical package (Muthén & Muthén, 1998–2012). Data were converted to Mplus format using the MplusAutomation package (Hallquist & Wiley, 2018). The decision to use 20 imputations was based on published recommendations (Graham, Olchowski, & Gilreath, 2007) and was consistent with the level of missing data (from 33% up to 66% of the data could be missing by design). Moreover, there would be minimal gain in power and trivial difference in the accuracy of parameter estimates with an increase to 40 imputed data-sets. By specifying the data source in Mplus as “imputation,” the procedure runs the analysis 20 times and averages the model parameters, accounting for missing data uncertainty (Rubin, 1987). This three-step approach of imputation, analysis, and pooling produces efficient and unbiased estimates is far superior to listwise deletion or other *ad hoc* methods (Graham, Hofer, & MacKinnon, 1996).

Model testing strategy

Model testing proceeded in three integrated steps. First, we ran latent class (LCA) analysis extracting from 2 to 8 classes using the 22 indicators and selected the best fitting model. The selection of the best model was based on the Akaike (1981) and Bayesian (Schwarz, 1978) Information Criterion, both of which penalize models for overparameterization (Nylund, Asparouhov, & Muthén, 2007). In both cases, lower values indicate better fit. In addition, we examined changes in the Log Likelihood (L^2) statistical fit index (McCutcheon, 1987). The L^2 statistic shows the amount of association among the indicators that is unexplained following model estimation, with smaller numbers indicating better fit. We also used the change in entropy, which provides an estimate of classification “uncertainty” based on the estimated posterior probabilities. The statistic ranges from 0 to 1, where higher numbers indicate less class misspecification (Celeux & Soromenho, 1996). In addition to the aforementioned statistical criteria, a key factor in choosing one model over another is that the resulting class structure is substantively meaningful; in other words, the class structure is interpretable, makes logical sense, and comports with real-world behaviors. Therefore, we carefully inspected the item response probabilities (i.e. the likelihood that members of a class endorsed an item) to determine whether they clearly distinguish uniquely identifiable and qualitatively discrete classes (Collins & Lanza, 2010). A cutoff of .60 was used for item response probabilities to determine the composition of a particular class. We did not consider

classes with less than 5% of the sample to avoid the possibility of sparse cells and convergence problems that can arise from weak identifiability (Garrett & Zeger, 2000). We also used 400 random starts for the initial stage and 100 for the final stage optimization to avoid obtaining a local maximum of the log-likelihood statistic.

Second, once we determined the best fitting LCA model, we examined the influence of covariates on class membership using multinomial logistic regression (MLR). This procedure determines whether there are distinct individual characteristics uniquely associated with class membership. We used the R3STEP utility available in the Mplus software (Asparouhov & Muthén, 2014; Vermunt, 2010) to test the covariate-adjusted models. This procedure, which represents an extension of the two-step classify-analyze approach (Bray, Lanza, & Tan, 2015), prevents the measurement parameters that help define class membership from being influenced by covariates, which should be structurally independent of the class measurement model. The R3STEP is a flexible step-wise procedure that estimates an unconditioned LCA model to compute the conditional probabilities for modal class assignment by producing a parameter representing the average classification error. Individuals are assigned to their most likely class based on the latent class posterior distribution. Then with the model measurement parameters fixed (i.e. thresholds expressed as logits), and accounting for measurement error in the class assignment process, the final model is conditioned by the covariates, adjusted for uncertainty in misclassification. For the MLR analyses, we present odds ratios (ORs) obtained from both unadjusted models examining each covariate individually and adjusted ORs with all covariates entered simultaneously as a block.

As a third and last step in model testing, we treated the three stress appraisal measures and two psychosocial measures as observed “distal” outcomes and allowed their means to vary across classes. Contrasting class-specific means (using a reference class with pairwise comparisons) represents another form of structural validity and treats the continuous markers as if they were “consequences” of class membership. To reduce the risk of Type I error due to multiple comparisons, we only conducted pairwise class comparisons contrasting a single reference class to the remaining classes. This approach allowed for meaningful, planned comparisons across classes.

Results

Results of the LCA models

Table 1 shows the model fit indices for the 2- to 8-class models. As expected, both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) progressively decreased with the additional

Table 1. Model Fit Statistics for Latent Class Analyses.

Classes	LL (deviance)	No. of free parameters	AIC	BIC	Relative entropy
2	−17822.22	45	35734.44	35970.14	0.824
3	−17282.64	68	34701.29	35057.45	0.829
4	−17034.99	91	34251.99	34728.63	0.846
5	−16864.69	114	33957.39	34554.49	0.851
6	−16658.69	137	33591.38	34308.96	0.854
7	−16538.41	160	33396.82	34234.87	0.852
8	−16471.91	183	33309.82	34268.33	0.844

Note: LL: log-likelihood statistics; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion. Model fit indices reflect mean values over 20 imputations adjusted for uncertainty. Relative entropy is a summary measure of classification certainty once posterior class probabilities are obtained and can be computed for $k > 1$ -class models. Some model fit statistics (e.g. Lo-Mendell-Rubin likelihood ratio test) are not available with imputed data.

extraction of classes. Entropy increased with an increasing number of classes and reached its highest value (0.854) at the 6-class model. We examined carefully both the 5- and 6-class models, both of which had excellent fit indices. The 6-class model provided better evidence of class enumeration based on the item response probabilities. That is, the extraction of an additional class in the 6-class model produced a sufficiently large group of individuals that combined various coping skills in a unique fashion and that was not evident in the 5-class model. In addition, item response probabilities in the 5-class model were moderately large in some cases but less than the desired benchmark, indicating that another class could be extracted with a more liberal cut-point (tabled values for the 5-class are available from the first author). The rate of shrinkage in the AIC and BIC also slowed down around the 6-class model. Classification probabilities for most likely class membership were 0.935 for Class 1, 0.914 for Class 2, 0.884 for Class 3, 0.877 for Class 4, 0.866 for Class 5 and 0.892 for Class 6.

Table 2 shows the item response probabilities for the 6-class model. Members of Class 1 (32.35%; “Resilient Flexible Problem-Focused Copers”) consisted of individuals with remarkably high probabilities of endorsement for all the items except for the emotion-focused coping items (i.e. venting). The average magnitude of endorsement for items exceeding the 0.6 benchmark was $\rho_{\text{avg.}}=0.858$, while the average endorsement probabilities for the emotion-focused coping items was lower ($\rho_{\text{avg.}}=0.194$). Class 2 (10.36%; “Resilient Inflexible Problem-Focused Copers”) endorsed the resilience items ($\rho_{\text{avg.}}=0.706$) as well as the problem-focused coping items ($\rho_{\text{avg.}}=0.802$). One problem-focused coping item (i.e. PF7; “compromise to get something positive from the situation”) had a much lower item response probability ($\rho = 0.470$). Also notable about this class was that its members had extremely low endorsement of the coping flexibility ($\rho_{\text{avg.}}=0.309$) and emotion-focused coping items ($\rho_{\text{avg.}}=0.174$).

Class 3 (13.34%; “Non-Resilient Flexible Problem-Focused Venters”) was characterized by high endorsement of coping flexibility as well as problem-

Table 2. Item Response Probabilities for the 6-Class Model.

	Latent class					
	1 Resilient Flexible Problem- Focused Copers 32.35%	2 Resilient Inflexible Problem- Focused Copers 10.36%	3 Non-Resilient Flexible Problem- Focused Venters 13.34%	4 Non-Resilient Flexible Problem- Focused Copers 19.71%	5 Non-Resilient Flexible Non-Copers 12.22%	6 Non-Resilient Inflexible Non-Copers 12.02%
Prevalence	32.35%	10.36%	13.34%	19.71%	12.22%	12.02%
RESIL1	0.857	0.732	0.287	0.351	0.634	0.197
RESIL2	0.858	0.738	0.111	0.155	0.513	0.106
RESIL3	0.836	0.633	0.175	0.186	0.522	0.104
RESIL4	0.905	0.782	0.220	0.097	0.507	0.105
RESIL5	0.720	0.684	0.293	0.252	0.468	0.199
RESIL6	0.776	0.664	0.212	0.096	0.470	0.037
CF1	0.914	0.516	0.757	0.773	0.708	0.242
CF2	0.843	0.530	0.759	0.715	0.630	0.257
CF3	0.944	0.072	0.882	0.860	0.764	0.067
CF4	0.969	0.180	0.868	0.883	0.895	0.164
CF5	0.907	0.248	0.842	0.829	0.724	0.234
PF1	0.959	0.841	0.789	0.889	0.307	0.465
PF2	0.878	0.800	0.765	0.833	0.270	0.482
PF3	0.899	0.850	0.723	0.855	0.371	0.530
PF4	0.942	0.841	0.841	0.878	0.243	0.458
PF5	0.814	0.738	0.762	0.751	0.206	0.361
PF6	0.809	0.744	0.701	0.722	0.382	0.484
PF7	0.605	0.470	0.494	0.456	0.274	0.244
EF1	0.118	0.073	0.976	0.007	0.127	0.278
EF2	0.238	0.229	0.789	0.126	0.171	0.279
EF3	0.113	0.110	0.803	0.190	0.119	0.375
EF4	0.305	0.284	0.726	0.462	0.318	0.495

Note. RESIL: resilience; CF: coping flexibility; PF: problem-focused coping; EF: emotion-focused coping. The bolded represent probabilities higher than 0.600.

and emotion-focused coping items, except for the one problematic problem-focused item (i.e. PF7) assessing the ability to compromise ($p = 0.494$). The average magnitude of the item response probabilities was relatively high for the coping flexibility items ($p_{\text{avg.}} = 0.822$), the problem-focused coping items ($p_{\text{avg.}} = 0.764$), and the emotion-focused coping items ($p_{\text{avg.}} = 0.824$), while endorsement for the resilience items was lower ($p_{\text{avg.}} = 0.216$). Class 4 (19.71%; “Non-Resilient Flexible Problem-Focused Copers”) endorsed all the coping flexibility items ($p_{\text{avg.}} = 0.812$) and 6 out of the 7 problem-focused coping items ($p_{\text{avg.}} = 0.821$). The magnitude of endorsement for the resilience items was lower ($p_{\text{avg.}} = 0.190$) and likewise for the emotion-focused coping items ($p_{\text{avg.}} = 0.196$). Class 5 (12.22%; “Non-Resilient Flexible Non-Copers”) endorsed only a single resilience item (“I tend to bounce back quickly after hard times”) ($p = 0.634$), and all of the coping flexibility items ($p_{\text{avg.}} = 0.744$). Item endorsement patterns for the problem-focused coping items were much lower in magnitude ($p_{\text{avg.}} = 0.293$), and likewise for the emotion-focused coping items ($p_{\text{avg.}} = 0.184$). Finally, Class 6 (12.02%; “Non-Resilient Inflexible Non-

Copers”) failed to endorse any one of the indicators above the .6 threshold ($\rho_{\text{avg.}}=0.280$).

Results of the correlational analyses

Table 3 shows the correlations among demographic measures, three subscales of stress appraisal, and two psychosocial measures. Among the demographic items, the largest associations were between age and education–earned degree ($r=0.47$), between living with family and living with non-family roommates ($r=-0.56$), and between earned degree and some schooling ($r=-0.46$), all in the expected direction. For stress appraisal, individuals who saw the pandemic as more impactful to their lives also saw it as uncontrollable ($r=0.24$) and more threatening ($r=0.41$). Those who saw it as more uncontrollable also saw it as more threatening ($r=0.28$). Only two demographic measures were associated with the stress appraisal subscales at $p<.001$: having some schooling and centrality ($r=-0.10$), and gender and threat ($r=-0.14$). Specifically, those who had less schooling were more likely to perceive the pandemic as impactful than those who had more schooling or were currently in college, and females were more likely to perceive the pandemic as a threat than males.

Older individuals and males engaged in less catastrophic thinking (r 's = -0.12 , -0.09 , respectively). Catastrophic thinkers were more likely to perceive the pandemic as impactful, uncontrollable, and threatening (r 's = 0.21 , 0.32 , and 0.32 , respectively). Impulsivity was related to higher levels of perceived consequence ($r=0.08$), uncontrollability ($r=0.14$) and catastrophic thinking ($r=0.20$). Overall, there was a clear indication that each of the stress appraisal and psychosocial measures captured unique facets of functioning with very modest overlap based on the zero-order associations.

Results of the multinomial logistic regression models: covariates of class membership

Table 4 shows the results of the MLR models. The upper portion of the table shows the unconditioned ORs in the univariate model where each covariate was entered individually, and the lower portion contains the ORs from the fully conditioned model with all covariates entered as a block using the R3STEP procedure. Class 1 (Resilient Flexible Problem-Focused Copers) served as the reference class. While any class can be used as the reference class, in the current study, Class 1 is the most prevalent (32.35%) and was characterized by the use of adaptive coping strategies: resilience, coping flexibility, and problem-focused coping. The ORs indicate the

Table 3. Associations Among Demographic and Psychosocial Measures Modeled as Covariates.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Age ^a	–											
2. Gender ^b	0.08**	–										
3. Race ^c	0.19***	0.00	–									
4. Job loss ^d	0.27***	0.11***	0.03	–								
5. RS–with family ^e	–0.02	–0.12***	–0.01	–0.09**	–							
6. RS–with roommate ^f	–0.10***	0.02	–0.05†	0.03	–0.56***	–						
7. ED–earned degree ^g	0.47***	0.06*	0.10***	0.30***	–0.04	–0.04	–					
8. ED–some schooling ^h	0.13***	0.00	0.01	–0.09**	0.01	0.06*	0.02	–				
9. SA–centrality ^a	–0.05	–0.06†	0.01	–0.11**	–0.10**	–0.10***	–0.10***	–				
10. SA–uncontrollability ^a	0.03	0.02	–0.08*	–0.02	–0.05	0.01	0.03	–0.02	–			
11. SA–threat ^a	–0.06	–0.14***	0.02	–0.07*	–0.05	0.03	–0.03	0.03	0.24***	–		
12. Catastrophic thinking ^a	–0.12***	–0.09**	–0.02	–0.08*	0.02	–0.05	–0.09**	0.03	0.41***	0.28***	–	
13. Impulsivity ^a	–0.06†	0.02	0.02	–0.10**	–0.01	0.03	–0.07*	0.02	0.21***	0.32***	0.32***	–
									0.08*	0.14**	0.06	0.20***

Note. RS: residential status; ED: education; SA: stress appraisal.

^aContinuous variables. ^bFemale = 0, Male = 1. ^cNon-White (including Latino/Latina/Latinxs)=0, While = 1. ^dNever having a job or keeping a job during the pandemic = 0, losing a job due to the pandemic = 1. ^eLiving alone or with non-family roommate(s)=0, living with family = 1. ^fLiving alone or with family = 0, living with non-family roommate(s)=1. ^gBeing in college or having limited or no postsecondary education = 0, having a postsecondary degree = 1. ^hBeing in college or having a postsecondary degree = 0, having limited or no postsecondary education = 1.

Numbers are point prevalence estimates averaging across the 20 imputed datasets. Nominal relations are parameterized as phi coefficients. Nominal and continuous relations are point-biserial Correlations. Continuous relations are Pearson product-moment correlations.

† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 4. Results of Multinomial Logistic Regression Predicting Class Membership.

	Latent class					
	1 Resilient Flexible Problem- Focused Copers 32.35%	2 Resilient Inflexible Problem- Focused Copers 10.36%	3 Non-Resilient Flexible Problem- Focused Venters 13.34%	4 Non-Resilient Flexible Problem- Focused Copers 19.71%	5 Non-Resilient Flexible Non-Copers 12.22%	6 Non-Resilient Inflexible Non-Copers 12.02%
Unadjusted odds ratio						
Age ^a	Ref	0.986	0.957 [†]	0.960 [†]	0.953 [†]	0.947 [†]
Gender ^b	Ref	0.995	0.282 ^{***}	0.682	1.203	0.740
Race ^c	Ref	1.329	1.219	1.156	0.876	0.957
Job loss ^d	Ref	0.662	0.504 ^{**}	0.673 [†]	0.594 [†]	0.639 [†]
RS-with family ^e	Ref	1.536	1.480	0.966	1.229	0.967
RS-with roommate ^f	Ref	0.483	0.847	0.940	0.964	0.861
ED-earned degree ^g	Ref	0.989	0.633 [†]	0.830	0.665	0.656 [†]
ED-some schooling ^h	Ref	1.018	1.186 ^{**}	1.083	1.161	1.198
SA-centrality ^a	Ref	0.770 [†]	1.675 ^{**}	1.318 [*]	0.765 [†]	1.045
SA-uncontrollability ^a	Ref	1.250	1.649 ^{**}	1.538 ^{**}	1.743 ^{**}	1.863 ^{***}
SA-threat ^a	Ref	0.812	2.476 ^{***}	1.781 ^{**}	0.833	1.297
Catastrophic thinking ^a	Ref	1.906 [*]	13.299 ^{***}	7.993 ^{***}	4.306 ^{***}	15.034 ^{***}
Impulsivity ^a	Ref	1.090	3.353 ^{***}	1.426 [†]	2.734 ^{**}	2.034 ^{**}
Adjusted odds ratio						
Age	Ref	0.978	1.020	0.983	0.980	0.985
Gender	Ref	1.099	0.329 ^{***}	0.775	1.149	0.749
Race	Ref	1.521	1.347	1.235	1.022	1.075
Job Loss	Ref	0.591 [†]	0.680	0.711	0.626	0.707
RS-with Family	Ref	1.257	1.502	0.878	1.189	0.785
RS-with Roommate	Ref	0.678	1.427	1.071	1.340	1.113
ED-earned degree	Ref	1.270	0.806	1.114	0.910	0.936
ED-some schooling	Ref	1.188	0.921	1.084	1.053	1.003
SA-centrality	Ref	0.720 [†]	1.119	0.971	0.630 [*]	0.758
SA-Uncontrollability	Ref	1.318	0.833	0.943	1.603 [*]	1.143
SA-threat	Ref	0.736	1.436 ^{**}	1.174	0.648 [†]	0.757
Catastrophic thinking	Ref	2.077 [*]	12.038 ^{***}	8.257 ^{***}	4.277 ^{***}	16.935 ^{***}
Impulsivity	Ref	0.996	2.456 ^{**}	1.070	2.228 [*]	1.365

Note: RS: residential status; ED: education; SA: stress appraisal.

^{abcd}Same as Table 3; ^eLiving alone = 0, living with family = 1; ^fLiving alone = 0, living with non-family roommate(s)=1; ^gBeing in college = 0; having a postsecondary degree = 1; ^hBeing in college = 0, having limited or no postsecondary education = 1.

Assignment to class is based on the most likely latent class membership, using the latent class posterior distribution. [†]90% Confidence Interval (CI) excludes 1.00; *95% CI excludes 1.00; **99% CI excludes 1.00; ***99.9% CI excludes 1.00.

strength of an association between a particular covariate (e.g. being male or perceiving threat) and membership in a designated class compared to the reference class.

As can be seen in the adjusted ORs from the lower portion of the table, males were less (or put differently, females were more) likely to be members of Class 3 (Non-Resilient Flexible Problem-Focused Venters) compared to Class 1 (Resilient Flexible Problem-Focused Copers).³ Although no other demographic measure significantly discriminated class membership in the adjusted model, age was marginally significant in the unadjusted model. To obtain a more refined picture of the role of age in class

membership, we tested a multiple group model using a cut-point of 25 years of age for comparison purposes (i.e. emerging adults ages 18–25 vs. younger adults ages 26–35). This model reinforced that there were slight, if not trivial, differences in the probabilities of class membership. However, these differences did not achieve significance, supporting the conclusion that the role played by age is minimal. Full analyses are available from the first author upon request.

For stress appraisal, centrality and uncontrollability, but not threat, were significantly related to class membership. Specifically, individuals who perceived the pandemic to be more central to their lives were *less* likely to be members of Class 5 (Non-Resilient Flexible Non-Copers) compared to the reference class. Individuals who perceived the pandemic to be more uncontrollable were *more* likely to be members of Class 5 (Non-Resilient Flexible Non-Copers), compared to the reference class.

The two psychosocial markers were also instrumental in differentiating class membership. Individuals who were *more* catastrophic in their thinking were more likely to be members of all five classes compared to the reference class. Specifically, compared to the reference class (Class 1; Resilient Flexible Problem-Focused Copers), those higher on catastrophic thinking were twice as likely to be Resilient Inflexible Problem-Focused Copers (Class 2), 12 times as likely to be Non-Resilient Flexible Problem-Focused Venters (Class 3), 8 times as likely to be Non-Resilient Flexible Problem-Focused Copers (Class 4), 4 times as likely to be Non-Resilient Flexible Non-Copers (Class 5), and almost 17 times as likely to be Non-Resilient Inflexible Non-Copers (Class 6).

Mean comparisons of structural validators

The fully conditioned MLR model configures the stress appraisal and psychosocial markers as covariates predicting class membership. Quite conceivably, membership in classes can be distinguished based on mean differences in these structural validators. This procedure models the intercepts of the structural validators for class and contrasts them using pairwise comparisons. Means of the structural validators were compared by contrasting the mean of Resilient Flexible Problem-Focused Copers (Class 1) to the remaining five classes.

For the stress appraisal markers, eight of the 15 pairwise comparisons were significant (refer to [Supplemental Table S.1](#) for the means, mean differences with confidence intervals, and effect sizes for the comparisons). For *centrality*, Resilient Flexible Problem-Focused Copers (Class 1, $M = 3.13$) had significantly *higher* scores than Resilient Inflexible Problem-Focused Copers (Class 2, $M = 2.83$: $t_{\text{diff}} = 0.30$, $SE = 0.15$, $p = .040$), and *lower*

scores than Non-Resilient Flexible Problem-Focused Venters (Class 3, $M = 3.64$: $t_{\text{diff}} = -0.51$, $SE = 0.19$, $p = .008$) and Non-Resilient Flexible Problem-Focused Copers (Class 4, $M = 3.44$: $t_{\text{diff}} = -0.31$, $SE = 0.14$, $p = .023$). For *uncontrollability*, Resilient Flexible Problem-Focused Copers (Class 1, $M = 2.20$) had significantly *lower* scores than Non-Resilient Flexible Problem-Focused Venters (Class 3, $M = 2.55$: $t_{\text{diff}} = -0.36$, $SE = 0.12$, $p = .002$), Non-Resilient Flexible Problem-Focused Copers (Class 4, $M = 2.51$: $t_{\text{diff}} = -0.31$, $SE = 0.12$, $p = .012$), and Non-Resilient Inflexible Non-Copers (Class 6, $M = 2.66$: $t_{\text{diff}} = -0.46$, $SE = 0.13$, $p = .001$). For *threat*, Resilient Flexible Problem-Focused Copers (Class 1, $M = 3.08$) had *lower* scores than Non-Resilient Flexible Problem-Focused Venters (Class 3, $M = 3.72$: $t_{\text{diff}} = -0.65$, $SE = 0.16$, $p < .001$), and Non-Resilient Flexible Problem-Focused Copers (Class 4, $M = 3.54$: $t_{\text{diff}} = -0.46$, $SE = 0.13$, $p < .001$).

Five of the 10 comparisons for the two psychosocial markers were significant. For *catastrophic thinking*, Resilient Flexible Problem-Focused Copers (Class 1, $M = 1.18$) engaged in *less* catastrophic thinking than Non-Resilient Flexible Problem-Focused Venters (Class 3, $M = 3.01$: $t_{\text{diff}} = -1.20$, $SE = 0.16$, $p < .001$), Non-Resilient Flexible Problem-Focused Copers (Class 4, $M = 2.71$: $t_{\text{diff}} = -0.90$, $SE = 0.11$, $p < .001$), and Non-Resilient Inflexible Non-Copers (Class 6, $M = 3.18$: $t_{\text{diff}} = -1.37$, $SE = 0.26$, $p < .001$). For *impulsivity*, Resilient Flexible Problem-Focused Copers (Class 1, $M = 2.37$) were *less* impulsive than Non-Resilient Flexible Problem-Focused Venters (Class 3, $M = 2.83$: $t_{\text{diff}} = -0.46$, $SE = 0.09$, $p < .001$) and Non-Resilient Flexible Non-Copers (Class 5, $M = 2.71$: $t_{\text{diff}} = -0.35$, $SE = 0.12$, $p = .003$).

Discussion

The findings of this study suggest that there are six qualitatively distinct typologies of coping, with the differences based on respondents' perceptions of their resilience, coping flexibility, and their use of problem-focused and emotion-focused coping strategies when facing a stressor (in this case, a global pandemic). The decision to retain the six-class model was based on a combination of statistical evidence in conjunction with substantive support. There was unambiguous evidence of latent class separation, particularly consistent and qualitatively distinct patterns of item response probabilities distinguishing the respective classes. For instance, members of the most prevalent class (Class 1; Resilient Flexible Problem-Focused Copers) endorsed all the indicators except for the emotion-focused (venting) coping items. By contrast, Non-Resilient Inflexible Non-Copers (Class 6) had exceptionally low endorsement probabilities for all of the indicators. Other evidence of latent class separation was apparent in that members of

the remaining four classes had high endorsement probabilities but only for a select group of items. For instance, Non-Resilient Flexible Problem-Focused Copers (Class 4), the second largest class, endorsed coping flexibility and problem-focused coping but did not endorse any of the resilience or emotion-focused coping items. This same pattern was evident for the smallest class, Resilient Inflexible Problem-Focused Copers (Class 2), who endorsed the resilience and the problem-focused coping items but no other items. This type of latent class separation with distinct patterns of item endorsement shows that the classes are composed of mutually exclusive types of individuals who employ dramatically different coping styles. Obtaining good latent class separation is an important feature of LCA model fit because statistical information by itself is insufficient to gauge model fit. Instead, the selection of the best-fitting model should be based on a combination of statistical information in concert with substantive knowledge and whether class composition reflects patterns that represent real-world behaviors (Collins & Lanza, 2010).

Interestingly, problem-focused coping was a central feature of four of the six classes including one that endorsed both problem- and emotion-focused coping. Problem-focused coping represents a set of cognitive and behavioral strategies used by individuals to reduce the negative effects of stress. Included in this repertoire of skills are active coping strategies that the individual uses to work through the problem, such as seeking information, finding different ways to extricate oneself from the situation, and weighing pros and cons of each. They are considered “active” because the individual focuses on dealing with the stressor rather than avoiding it. In contrast to problem-focused coping, emotion-focused coping was highly endorsed only by members of the Non-Resilient Flexible Problem-Focused Venters class (Class 3; 13.34%), suggesting that they are the only ones who are expressive when experiencing negative emotions in the face of stress. Overall, the interdependence or balance between problem- and emotion-focused coping is what Folkman and Lazarus (1980; Lazarus, 2000) envisioned in their original theoretical conceptualization and dovetails with what unfolds in ordinary day-to-day living.

Resilience, which captures the ability to bounce back after facing a setback, also played a key role in distinguishing class membership. In one case (Class 1), participants endorsed the resilience items in concert with both coping flexibility and problem-focused coping, representing a resourceful and high-functioning class. In the other case (Class 2), individuals saw themselves as being resilient and applying problem-focused coping skills but not as flexible or relying on venting when stressed. Notably, Non-Resilient Flexible Non-Copers (Class 5) fell short of the desired benchmark (<0.6) to be considered resilient, except for one item (“I tend to bounce

back quickly after hard times,”; $p = 0.634$). Otherwise, this would have created a class distinguished based on being resilient and flexible but not applying other coping skills.

Coping flexibility was also instrumental in defining class membership. The indicators of this skill were endorsed in four of the six classes, which reflects the importance of shifting strategies in response to stress. In effect, effective coping is not based on an “either-or” approach, but rather careful evaluation of what strategies are most appropriate to deal with the stressor. Moreover, we argue that focusing only on problem- and emotion-focused coping is unrealistic given that the nature of a stressor (primary appraisal) and individual resources (secondary appraisal) determine which strategies individuals will apply, reinforcing the “transactional” nature of coping proposed by Lazarus and Folkman (1984). Indeed, the ability to be more adaptive and shift back and forth between coping skills (i.e. flexibility) may be an important distinguishing feature of how successful a person is when dealing with stressful and dynamic situations like the pandemic. The disruptive nature of the pandemic, which caused a rapid increase in unemployment rates, forced school closures, and contributed to major lifestyle changes, may require individuals to be flexible in choosing how to respond to stress and be willing to switch to another coping strategy if the current one is not working.

The second aim of this study was to determine whether certain factors could distinguish class membership. This represents a form of structural validation (i.e. substantive checking), assessing whether class membership differs in characteristically unique ways that extend beyond the indicators. Interestingly, both the unadjusted and adjusted models reinforced that the composition of the different classes was largely independent of the demographic measures. Only gender was a significant predictor in the adjusted model. Specifically, females were over three times as likely (i.e. $1.000/0.329 = 3.040$) to belong to the Non-Resilient Flexible Problem-Focused Venters class (Class 3) than the reference class. The lack of significant association of coping styles with education was somewhat surprising as decision-making and problem-solving skills are usually honed and refined with more advanced education and contribute to more adaptive coping. Similarly, living with roommates or family members would be expected to provide much-needed social support and help individuals to cope with stressful events, yet there was no association between living arrangement and class membership.

The inclusion of stress appraisal and psychosocial markers painted a completely different picture, however. All three of the stress appraisal measures helped to discriminate class membership in the unadjusted model. Compared to the high-functioning reference class (Resilient Flexible

Problem-Focused Copers), participants who saw the pandemic as more impactful, uncontrollable, or threatening were more likely to be members of Class 3 (Non-Resilient Flexible Problem-Focused Venters) and Class 4 (Non-Resilient Flexible Problem-Focused Copers). Further, those who saw the pandemic as more uncontrollable were more likely to be members of Class 5 (Non-Resilient Flexible Non-Copers) and Class 6 (Non-Resilient Inflexible Non-Copers). However, the influence of stress appraisal waned when the measures of psychosocial functioning and demographics were included in the fully adjusted model. In the fully adjusted model, those who saw the pandemic as more impactful were less likely and those who saw the pandemic as more uncontrollable were more likely to be members of Class 5 (Non-Resilient Flexible Non-Copers) than the reference class.

The two measures of psychosocial functioning also played an important role in discerning class membership. All told, seven of the possible 10 adjusted ORs were significant, five of which involved catastrophic thinking. In all five instances, members of the different classes were more likely to be catastrophic thinkers compared to the reference class. This suggests that individuals who perceive negative events as stable (across time), global (affecting more than one facet of their life), and their fault, may let their negative attributions interfere with their coping processes. Indeed, the ORs were exceptionally large for members of Non-Resilient Flexible Problem-Focused Venters (Class 3; OR = 12.038) and Non-Resilient Inflexible Non-Copers (Class 6; OR = 16.935). Impulsivity also factored into membership in Non-Resilient Flexible Problem-Focused Venters (Class 3) and the Non-Resilient Flexible Non-Copers (Class 5), suggesting that members of these classes are more likely to make rash decisions than Resilient Flexible Problem-Focused Copers.

An additional form of structural validation of the classes was provided by comparing the means of the external markers (i.e. the three subscales of stress appraisal, catastrophic thinking, and impulsivity) across classes (i.e. in comparison to the reference class). All classes (2–6), were distinguished from the reference class by at least one external marker. Notably, Class 3 (Non-Resilient Flexible Problem-Focused Venters), of which females were more likely to be members, had significantly higher means for all external markers compared to the reference group (see [Table S.1](#)). These results provide further evidence that class membership differs in characteristically unique ways that extend beyond the indicators.

Study limitations

This study has several limitations worth mentioning. First, given the cross-sectional nature of this data, we cannot draw causal conclusions. Temporal

precedence is required to provide causal support; therefore, we cannot know whether stress appraisal or psychosocial characteristics are causes or effects of coping strategies when applied in direct response to the pandemic. Moreover, the sampling frame used may introduce a modicum of bias into the results, as we used an online marketplace (MTurk) that attracts individuals looking for ways to earn money as survey respondents. This data collection approach could potentially eliminate certain respondents, thus introducing bias. Notwithstanding, recent studies reinforce that, compared to other survey formats, web-based surveys can produce well-balanced heterogeneous sample pools (e.g. Evans & Mathur, 2005), somewhat alleviating concerns about this method of data collection.

The timing of the data collection may also have influenced the results. We started the data collection in late-April to early-May, anticipating that the pandemic might be better controlled by the end of the summer; however, the pandemic extended over a longer period. Facing a persistent (and ever-changing) stressor like the pandemic and facing a cascade of related disruptions may cause some individuals to abandon certain coping strategies, apply others, and/or resort to different coping strategies, which can be due to psychological fatigue (Morgul et al., 2020). An interesting alternative approach, though difficult to execute, is to examine coping styles before, during, and after the pandemic to determine the durability of coping skills. A study like the one by Zacher and Rudolph (2020) with a retrospective reporting design or a longitudinal design opportunistically capitalizing on staged data collection during the event could address changes in coping style with a singular, unprecedented event like the pandemic.

Although the analyses were powered for person-centered strategies using the full sample, the sample size precluded testing invariance by gender, race, or other demographic factors. Mixture models require larger samples to obtain stable parameter estimates, which we could not have with 6 classes split among observed subgroups (Nylund et al., 2007). We also considered only a subset of problem- and emotion-focused coping strategies. However, there is now substantial evidence to suggest that additional strategies including avoidance, meditation, help seeking, distraction, and emotion suppression are viable coping strategies (Folkman & Moskowitz, 2004). The inclusion of a wider set of coping strategies in concert with a larger sample to obtain appropriate power for the LCA models is certainly warranted. The same holds for racial/ethnic comparisons; we collapsed all racial/ethnic minority groups into the “non-White” group given their small sample sizes. Future analyses with larger samples should examine whether class structure varies by race/ethnicity, particularly given the evidence of

racial disparity in the health effects of the pandemic (Hooper, Nápoles, & Pérez-Stable, 2020; Selden & Berdahl, 2020).

We also used the Resilient-Flexible Problem-Focused Copers (Class 1) as the reference class both in the MLR and in the analyses examining mean differences in the external markers. There would be 75 possible pairwise comparisons in a traditional ANOVA framework; however, using one class as the reference class reduced the number of comparisons to a more manageable set and avoided chance findings. Even though this strategy reduced the possibility of making Type I errors with false positives, it still came at the expense of discovering other comparisons that may have revealed unique forms of vulnerability.

Finally, we did not ask participants whether they had been tested for and had contracted COVID-19. Even though viral load tests were not as ubiquitous when the survey was conducted in late-April to early-May, such information could have been valuable to discern how their direct experience with the virus would play a role in their coping. We also did not ask participants about their precise occupation. There is evidence suggesting that people with service-related jobs are at higher risk of contracting the virus (Baker, Peckham, & Seixas, 2020). The way we measured stress appraisal was designed to capture risk “at a distance,” rather than actual risk *per se*. Even though we collected data on job loss due to the pandemic, information on occupational types might have provided a more direct measure of risk for infection or other pandemic-related stressors that influence stress appraisal and coping.

Conclusion

The current study provided valuable insight into different coping styles of young adults and how these styles relate to perception of the pandemic as well as psychosocial functioning. The results replicated past studies regarding effectiveness of problem-focused coping (Folkman & Moskowitz, 2004; Lazarus & Folkman, 1987), but more importantly, the study’s unique contribution was to demonstrate vital roles that both resilience and coping flexibility play in adaptive coping. Indeed, those who were either only resilient or only flexible while applying problem-focused coping (Class 2 and Class 4, respectively) did not appear to be responding to the pandemic as effectively as those who were both resilient and flexible (Class 1). This finding calls for programs emphasizing stress-management and self-regulation skills in young adults and teaching them how to avoid dwelling on negative thoughts and reframe unproductive and self-defeating thoughts. Online-based psychotherapy such as

cognitive behavioral therapy via self-paced online modules and telehealth can be a cost-effective way to deliver time-sensitive treatment (Ho, Chee, & Ho, 2020; Reay, Looi, & Keightley, 2020; Zhang & Ho, 2017).

Young adults, compared to other age groups, can be uniquely vulnerable to the psychosocial effects of the pandemic given a variety of restrictions on their autonomy. This can interfere with the individuation process whereby they make choices that help construct their life course (Arnett, 2015). In attempts to minimize restrictions on their autonomy and regain a sense of autonomy and control, young adults could potentially engage in behaviors that contribute to the spread of the virus, such as attending a large in-person gathering without wearing a mask. On the other hand, loss of perceived autonomy and control could also contribute to mental health issues such as depression that could adversely affect their functioning (Inguglia, Ingoglia, Liga, Coco, & Cricchio, 2015). Therefore, further inquiry on unique ways in which young adults cope with stress and how it can affect their psychological and behavioral adjustment can better prepare educators and clinicians to train them to be effective copers in face of unprecedented stressors like pandemics.

Notes

1. Universities and colleagues were approached by all the four authors involved in this project via email. These individuals in turn spread the word about the study to their friends and peers. Some of the college students who completed our survey may be outside the PI/first author's institution, but we did not keep record.
2. The demographic characteristics of the two groups of participants were compared. Participants recruited through MTurk were older; more likely to be female; more likely to be White, Non-Hispanic/Latino/a/x; more likely to have lost a job due to the pandemic; more likely to live alone and less likely to live with a roommate or family; and more likely to have only attended some school (some college or less), more likely to have earned a degree (undergraduate or graduate), and less likely to be current students (undergraduate or graduate). All of these demographic measures were included as model covariates.
3. Significance of the MLR portion of the analysis is based on the *p*-values of the logits, the confidence intervals of the logits, and the exponentiated confidence intervals of the logits (i.e. asymmetric confidence intervals of the ORs) which give equivalent results. The *p*-values for the ORs were not used because ORs may not be normally distributed leading to biased tests.

ORCID

Aya Shigeto  <http://orcid.org/0000-0002-3127-3162>

Daniel J. Laxman  <http://orcid.org/0000-0002-5505-9806>

Justin F. Landy  <http://orcid.org/0000-0002-4082-9505>

Lawrence M. Scheier  <http://orcid.org/0000-0003-2254-0123>

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