Affective Science
https://doi.org/10.1007/s42761-025-00322-z

RESEARCH

Testing Models of Resilience in University Students: A Multi-Site Study

Ellen Jopling[1,2,16] · Taylyn Jameson[1] · Stevi G. Ibonie[3] · Gerald Young[4] · Iris B. Mauss[5] · Lauren B. Alloy[6] · Jessica L. Borelli[7] · Ben Bullock[8] · Sarah R. Holley[9] · Shanmukh Kamble[10] · Liam Mason[11] · Daniel P. Moriarity[12] · Robin Nusslock[13] · Amie Okuma[11] · Robb B. Rutledge[11,14] · Gregory P. Strauss[15] · Cynthia M. Villanueva[3] · June Gruber[3] · Joelle LeMoult[1]

Received: 10 September 2024 / Accepted: 15 July 2025

Abstract

Emerging adulthood is characterized by marked increases in vulnerability to psychiatric illness. As such, understanding how risk and protective factors function to promote, or impede, resilience during early adulthood is critical. This pre-registered work is the first to test four leading models of resilience among emerging adults. A sample of 1,075 participants drawn from four international university sites were followed across two stressors: the transition to university (cross-sectional) and the COVID-19 pandemic (longitudinal). We found support for the compensatory model, which holds that risk and protective factors contribute additively to predict resilience, at both timepoints. Findings also support the risk-protective model, but only during the university transition, indicating that the influence of risk factors on negative outcomes during the university transition is buffered by protective factors. Neither the challenge nor protective-protective models were supported. Results have the potential to guide theory development by highlighting the dynamic nature of resilience and have implications for prevention and intervention efforts by underscoring the powerful influence of protective factors.

Keywords Emerging adulthood · Protective factors · Resilience · Risk factors · Stress

Emerging adulthood is a developmental period involving a series of ubiquitous and normative challenges that increase vulnerability to psychiatric disorders (Arnett 2000, 2007). Indeed, rates of psychiatric disorders increase substantially during emerging adulthood, which spans the ages of 18 to 25 years (Auerbach et al., 2016). Yet, many individuals do not develop psychopathology during this period and instead demonstrate resilience (i.e., an ability to adapt successfully to challenging circumstances; Luthar 2006; Masten et al., 1990). Central to understanding and ultimately promoting resilience includes elucidating the ways in which risk and protective factors influence resilience among emerging adults.

Although resilience historically has been conceptualized as a static trait, there is a burgeoning understanding of resilience as a dynamic and multi-faceted process that can

Handling Editor: Renee Thompson

June Gruber and Joelle LeMoult are co-principal investigators

✉ Ellen Jopling
ellen.jopling@childrens.harvard.edu

1 University of British Columbia, Vancouver, Canada
2 University of British Columbia, Harvard Medical School, Boston Children's Hospital, Boston, USA
3 University of Colorado, Boulder, USA
4 Ohio University, Athens, USA
5 University of California, Berkeley, USA
6 Temple University, Philadelphia, USA
7 University of California, Irvine, USA
8 Swinburne University of Technology, Hawthorn, Australia
9 San Francisco State University, San Francisco, USA
10 Karnatak University, Dharwad, India
11 University College London, London, UK
12 University of Pennsylvania, Philadelphia, USA
13 Northwestern University, Evanston, USA
14 Yale University, New Haven, USA
15 University of Georgia, Athens, USA
16 Department of Pediatrics, Boston Children's Hospital, Boston, USA

Published online: 26 August 2025

be promoted or impeded across time (Masten et al., 2021). Further, in the same way that defining health should not capture solely the absence of disease, there is a growing consensus that assessments of resilience should include aspects of healthy psychological functioning, such as subjective happiness and well-being (Bonanno et al., 2004; Southwick et al., 2014). As such, resilience can be conceptualized as a multi-factorial outcome that involves well-being, subjective happiness, and the absence of psychopathology (e.g., Seery, 2011; Troy et al., 2023).

Critical life transitions offer an ideal naturalistic window to investigate resilience in the real world, given that they present an inherent need for adaptation. Emerging adulthood is rich in developmental life transitions, and investigations during this period provide an opportunity to understand factors that promote or impede resilience during life transitions. One common and often challenging transition during emerging adulthood is the transition to university, wherein many students experience academic, social, and financial challenges (Bayram & Bilgel, 2008; Rahat & Ilhan, 2016). Indeed, the university transition is a time when psychological distress markedly increases, and both risk (e.g., perceived stress) and protective factors (e.g., social support) influence resilience (Brett et al., 2022; Leary & DeRosier, 2012). Critically, students who transitioned to university during the 2019/2020 academic school year faced an additional challenge: the COVID-19 pandemic (Gruber et al., 2021). The pandemic necessitated extensive measures including sheltering in place, social isolation, and a sudden transition to online learning. Many also experienced a loss of income, health-related worries, and the loss of loved ones (Browning et al., 2021). In line with life-course theory, which emphasizes the importance of the timing and context of major life events (Elder, 1985), the successive nature of these stressors may have exacerbated existing adaptational difficulties. Given the potential for pathways of well-being to become established during emerging adulthood (Masten et al., 2006), we must understand the processes through which risk and protective factors promote or impede resilience during this developmental period.

Four leading models of resilience exist in the literature, each of which posits different relations between risk and protective factors in predicting resilience amidst adversity (see Fig. 1). The first is the *compensatory model*, which suggests

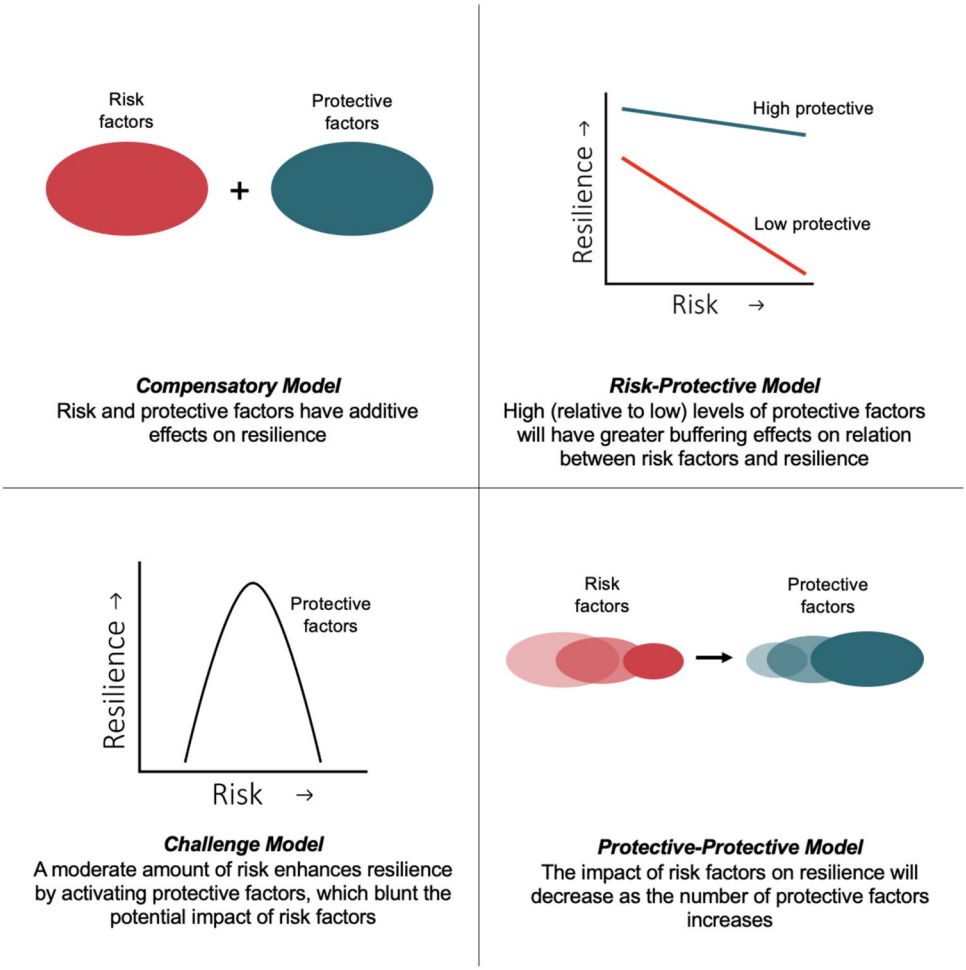

Fig. 1 Visual depiction and description of models of resilience

that risk and protective factors have additive and independent effects on adjustment, with risk factors decreasing resilience and protective factors increasing resilience (Garmezy et al., 1984; Rutter, 1985). The second is the *risk–protective model*, which suggests that resilience is related to the interaction effect between risk and protective factors such that, relative to low levels of protective factors, higher levels will have greater buffering effects on the relation between risk factors and resilience (Dubow & Luster, 1990). The third model is the *challenge model*, which suggests a curvilinear relation wherein a moderate amount of risk enhances resilience by activating protective factors, which blunt the potential impact of risk factors (Garmezy et al., 1984). The fourth model, the *protective–protective model*, is a variation on the risk-protective model that posits protective factors are not just buffers against risk but are part of a dynamic interaction wherein the presence of multiple protective factors can compound each other's positive effects (Hollister-Wagner et al., 2001).

Several recent studies have tested which model(s) best predict resilience among emerging adults (Goldstein et al., 2013; Heinze et al., 2020; Oginni et al., 2020). This preliminary work broadly has indicated support for the compensatory model, while the risk-protective model has received mixed support. However, this work has examined resilience in unique contexts, such as the transition out of child welfare (Goldstein et al., 2013) and discrimination among LGBTQIA + emerging adults in Nigeria (Oginni et al., 2020). Beyond the emerging adulthood period, there has been some work in support of the compensatory and risk-protective models among both children and adults (Anyan & Hjemdal, 2016; Askeland et al., 2020; Evans et al., 2010; Hurd et al., 2009). For instance, the compensatory and risk-protective models have been supported in the context of risk for adolescent substance use (Pisarska et al., 2016) and among rural male farmers (McLaren & Challis, 2009). Further, although the protective-protective and challenge models have garnered mixed support in both the child and adult literature to date, they have yet to be tested in emerging adulthood. As such, prospective research is needed that simultaneously tests all four models during emerging adulthood.

The present study extends previous work by testing four models of resilience among emerging adults across two ubiquitous, naturalistic, and successive stressors: the transition to university and the COVID-19 pandemic, which exacerbated mental health concerns among emerging adults (Gruber et al., 2023). Taking an ecological system theory approach (e.g., Bronfenbrenner, 1979), we will examine risk and protective factors across domains of functioning. In line with previous work, we will examine factors across the *individual*, *school*, *family/community*, and *peer/social* domains (Evans et al., 2010). Specifically, for each domain, we developed empirically derived indices of risk and protective factors to test the four resilience models and to identify which model(s) explain levels of resilience across time.

We assessed risk and protective factors during students' first 6 months at their respective university (sampled across four sites spanning Europe and North America to enhance generalizability) and then followed them across their first year of university. In line with current conceptualizations, resilience was operationalized as a latent factor composed of well-being, subjective happiness, and the absence of psychopathology. Based on previous work and in line with the compensatory model, there is reason to expect that both risk and protective factors will have direct and independent roles in predicting resilience over time. In addition, there is reason to believe that an interactive association between risk and protective factors will emerge, though there is insufficient empirical evidence within emerging adults to hypothesize whether this association will be buffering (i.e., risk-protective model), curvilinear (i.e., challenge model), or additive (i.e., protective-protective model) in nature. In other words, although we anticipate that risk and protective factors will interact to influence resilience, we do not yet have enough information to predict the nature of that interaction in emerging adults.

Method

Participants

First-year university students ($N = 1{,}075$) between 18 to 25 years of age were recruited from four sites in Europe and North America: the University of Colorado, Boulder ($n = 658$), the University of British Columbia ($n = 211$), University College London ($n = 139$), and Temple University ($n = 67$). This sample, which was drawn from a larger multi-site project, represents the subsample of participants who completed the measures of interest, which were only administered at these four study sites. The initial project stemming from this broader multi-site study is published in the *Journal of Social and Clinical Psychology* (Ibonie et al., 2025). The sample had a mean age of 18.35 ($SD = 0.61$; range = 18 to 23) years. The majority of participants identified as women (76%), followed by men (23%), and transgender or non-binary (0.5%). Regarding racial identity, the majority of participants identified as White (56%; $n = 600$) or Asian (26%; $n = 281$), followed by Latinx/e-White (4%; $n = 41$), Latinx/e (3.7%; $n = 40$), Asian-White (3.1%; $n = 34$), and Black (1.9%; $n = 21$). See onlinesupplement for further details.

Table 1 Descriptive statistics for resilience indicators

	Transition to university	COVID-19	*t*	*p*
Satisfaction with Life (SWLS), M (SD)	4.57 (1.33)	4.48 (1.38)	−0.38	.701
Subjective Happiness (SHS), M (SD)	18.12 (5.16)	17.99 (5.45)	−1.31	.190
Psychopathology (DSM-5 CC), M (SD)	20.23 (13.64)	18.55 (12.88)	−3.90	<.001

Descriptive statistics are presented for the DSM-5 CC prior to reverse scoring, such that higher values indicate higher levels of psychopathology

Measures

Resilience Factors

Following recommendations put forth by Bonanno (2004) and others (e.g., Seery, 2011; Southwick et al., 2014), resilience was conceptualized as a latent variable composed of three measures including life satisfaction, subjective happiness, and the absence of psychopathology. Descriptive statistics for these scales are presented in Table 1. Life satisfaction was indexed with the 5-item Satisfaction with Life Scale (SWLS; Diener et al., 1985). Global subjective happiness was indexed via the 4-item Subjective Happiness Scale (SHS; Lyubomirsky & Lepper, 1999). The absence of psychopathology symptoms was indexed via the 23-item DSM-5 Self-Rated Level 1 Cross-Cutting Symptom Measure (DSM-5 CC; American Psychiatric Association, 2013). In line with previous work (Harvey et al., 2021), items were reversed-scored and summed; thus, higher scores indicate less psychopathology.

SWLS Satisfaction with Life Scale, *SHS* Subjective Happiness Scale, *DSM-5 CC* DSM-5 Self-Rated Level 1 Cross-Cutting Symptom Measure.

Risk Factors

Consistent with prior work, a cumulative risk index was created by calculating the number of ecological domains in which an individual had a risk factor (Atkinson et al., 2015; Ostaszewski & Zimmerman, 2006). Drawing from prior research focused on risk factors in emerging adulthood, within the individual domain, we assessed perceived stress (Perceived Stress Scale; Cohen et al., 1983) as high perceived stress is a well-documented risk factor capturing cognitively mediated appraisals of general stress and is linked to poor social and emotional well-being (Anastasiades et al., 2017; Xia & Ma, 2020). Within the school domain, we assessed first-generation student status (using a single item generated in-house: "Are you a first-generation university student?") as this is an established risk factor for increased mental health difficulties during emerging adulthood (House et al., 2020; Jenkins et al., 2013). Regarding family/community factors, we assessed family history of mental illness (Family Index of Risk for Mood; Algorta et al., 2013), which has been robustly linked with psychopathology among emerging adults and university students (Ensminger et al., 2003; Mitchell et al., 2018). Finally, within the peer/social domain, we measured recent aggressive and/or illegal behavior (Cognitive Appraisal of Risky Events scale; Fromme et al., 1997), as the emerging adult literature highlights interpersonal risk preference—indexed by interpersonal aggressive and illegal behaviors—as a particularly important risk factor associated with decreased resilience (Gros et al., 2010; Modecki, 2016).[1]

Consistent with previous work both in the fields of resilience (e.g., Evans et al., 2010; Hollister-Wagner et al., 2001) and allostatic load theory (Juster et al., 2010), individuals were assigned a score of 1 when the relevant risk factor was present, if they responded affirmatively to a dichotomous item, or if they scored in the most extreme quartile on a continuous scale (at or above the 75th percentile). Scores then were tallied such that each individual received a cumulative risk index value ranging from 0 (no risk factors) to 4 (risk factors present across all four domains). Descriptors of risk variables are presented in Table 2.

Protective Factors

The cumulative protection index was created by calculating the number of ecological domains in which an individual had a protective factor. Protective factors were empirically derived from previous work examining risk and protective factors in emerging adulthood. Specifically, within the individual domain, we measured responsiveness to reward (reward responsiveness subscale of the Behavioural Approach System Scale; Carver & White, 1994), which has emerged as a critical protective factor associated with adaptive functioning among emerging adults (Corral-Frias et al., 2016; Taubitz et al., 2015). Within the school domain, we assessed academic self-efficacy (Academic Self-Efficacy

[1] Although perceived stress and aggressive/illegal behavior at times have been operationalized as outcomes in prior work, in the current study, these variables were included as risk factors given evidence indicating that these factors prospectively predict pernicious outcomes across multiple domains, including social functioning and psychological well-being (Ehrenreich et al., 2016; Huesmann et al., 2009).

Table 2 Descriptors of risk and protective variables

Variable	Domain	Criterion	
Risk variables			% at-risk
Perceived stress	Individual	≥ 75th percentile	28.8
First-generation student status	School	Yes	19.1
Family history of mental illness	Family/community	Yes	61.3
Risk preference	Peer/social	≥ 75th percentile	35.6
Protective variables			% protected
Responsiveness to reward	Individual	≥ 75th percentile	28.6
Academic self-efficacy	School	≥ 75th percentile	27.4
Belongingness at university	Family/community	≥ 75th percentile	26.1
Social support	Peer/social	≥ 75th percentile	44.7

Scale; Gaumer Erickson et al., 2018), which is linked to greater well-being and better adjustment in university students (Chemers et al., 2001; Grøtan et al., 2019). Next, within the family/community domain, we assessed belongingness at university (Belonging Uncertainty Scale, reverse coded such that a higher score indicates a greater sense of belongingness at an individual's university; Walton & Cohen, 2007), as feelings of university belongingness are associated with greater mental health and well-being among university students (Gopalan et al., 2020; Suhlmann et al., 2018). Finally, within the peer/social support domain, we measured social support (Perceived Social Support Scale; MIDUS II), which is a well-recognized protective factor associated with increased resilience among emerging adult populations (Taylor et al., 2014).

In line with previous work (Evans et al., 2010; Hollister-Wagner et al., 2001), individuals were assigned a score of 1 when the relevant protective factor was present, if they responded affirmatively to a dichotomous item, or if they scored in the most extreme quartile on a continuous scale. These scores then were summed such that each individual was assigned a cumulative protective index value ranging from 0 (no protective factors) to 4 (protective factors present within each domain). Descriptors of protective variables are presented in Table 2.

Procedure

Participants were recruited Fall 2019, during their first semester of university and before the onset of the COVID-19 pandemic. At this baseline timepoint, participants reported on risk and protective factors and resilience measures. We then followed participants longitudinally, across their first year of university, and collected a second assessment of resilience Spring 2020 (between March 30 and June 1, 2020), following the onset of the pandemic and when the strictest physical-distancing measures of the COVID-19 pandemic's first wave were in place. There was a mean of 148.61 days ($SD = 56.85$) between timepoints.

Analytic Plan

Data were analyzed using a pre-registered analytic plan (https://aspredicted.org/ZWC_4XW). Preliminary analyses involved conducting correlational analyses examining associations between risk and protective terms and resilience at both timepoints. Competing models of resilience then were tested using a multistage factor score regression approach (Hayes & Usami, 2020; Hoshino & Bentler, 2013). In factor score regression, factor scores from a measurement model are created for each construct of interest separately and saved in the first step. In a second step, the factor scores are treated as observed data in a subsequent regression analysis.

Thus, in the first step, we extracted scores on latent factors representing levels of resilience during the university transition and the COVID-19 pandemic. To model resilience during the university transition and COVID 19-pandemic, a latent factor was developed using the "lavaan" packages for R (Rosseel, 2012) by regressing scores from the SWLS, SHS, and DSM-5 CC (reverse scored) during each timepoint (i.e., university transition or COVID-19 pandemic) on a higher-order factor representing levels of resilience at that timepoint. The SHS was set as the marker variable across models (i.e., loadings fixed to 1; Kline, 1998). Scores on each of these latent factors then were extracted. Next, using a hierarchical regression approach outlined by Evans et al. (2010), Garmezy et al. (1984), and Hollister-Wagner et al. (2001), we employed the empirically derived risk and protective indices described above to test the four models of resilience: the compensatory model, the challenge model, the risk-protective model, and the protective-protective model. In this approach, the main effect for risk is entered in Block 1.[2] The main effect for protection then is entered

[2] A "block" refers to a step in the hierarchical regression analysis where predictors are entered into the model in a sequential manner. This approach quantifies the unique contribution of each group of variables to the overall model while controlling for previously entered predictors.

in Block 2; main effects for both risk and protection are subsequently interpreted in Block 2. Significance of both of these indices provides support for the compensatory model. Next, a risk × protection interaction term is entered in Block 3, and significance of this term provides support for the risk-protective model. Finally, a quadratic effect of risk (i.e., risk × risk interaction term) is entered in Block 4 and is meant to capture potential non-linear relationships between risk and resilience. The significance of the risk × risk term in Block 4 provides support for the challenge model. The significance of the risk × protection term in Block 4 (when the risk × risk term also is included in the model, which allows for the examination of how protective factors may dynamically attenuate various levels of risk) provides support for the protective-protective model.[3] Two separate analyses were conducted in which risk and protective factors assessed during the university transition predicted (1) resilience during the university transition (cross-sectional) and (2) resilience during the subsequent COVID-19 pandemic (longitudinal). Significant interactions were explored through simple slopes analyses and calculation of regions of significance using the Johnson-Neyman technique (Bauer & Curran, 2005).

Transparency and Openness

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study. Data were analyzed using R, version 4.3.1 (R Core Team, 2023). Data, materials, and analysis code are available upon request to the corresponding author. Readers are encouraged to access the online supplement for details related to the broader multi-site project from which the data stem. This study's design and hypotheses were preregistered after data had been collected but before analyses were undertaken; see https://aspredicted.org/ZWC_4XW. Deviations from the preregistration are outlined in the online supplement.

Results

Preliminary Analyses

Resilience across timepoints was associated with risk and protective terms in the expected directions. Specifically, resilience was positively correlated with the cumulative protection index during the university transition, $r = .40$, $p < .001$, 95% CI [0.35, 0.45], and COVID-19 pandemic, $r = .33$, $p < .001$, 95% CI [0.24, 0.40]. Similarly, resilience was negatively correlated with the cumulative risk index during the university transition, $r = -.38$, $p < .001$, 95% CI [−0.43, −0.32], and COVID-19 pandemic, $r = -.33$, $p < .001$, 95% CI [−0.40, −0.24]. Correlations between key study variables are presented in the online supplement.

Table 3 Predicting resilience during the university transition

Variable	*B*	*β*	*SE B*	*p*	95% CI
Risk *Block 2*	−1.19	−.31	.10	<.001	−1.40, −0.99
Protective *Block 2*	1.38	.34	.11	<.001	1.17, 1.59
Risk × protective *Block 3*	0.22	.10	.11	.042	0.01, 0.44
Risk × protective *Block 4*	0.17	.08	.11	.125	−0.05, 0.40
Risk × risk *Block 4*	−0.15	−.13	.09	.090	−0.32, 0.02

Measurement Model

A measurement model was developed for resilience during the university transition. This model was just-identified, and therefore, only AIC (17,841.47) and BIC (17,871.35) were estimated. Standardized loadings for the resilience factor were .80, .82, and .67 (for the SWLS, SHS, and DSM-5 CC, respectively). R-square estimates were .64 (SWLS), .67 (SHS), and .45 (DSM-5 CC). We then developed a measurement model for resilience during the COVID-19 pandemic. This model also was just-identified (AIC = 8216.71, BIC = 8241.81). Standardized loadings were .76, .80, and .59 (for the SWLS, SHS, and DSM-5 CC, respectively). R-square estimates were .57 (SWLS), .65 (SHS), and .35 (DSM-5 CC). Comparisons between resilience indicators across timepoints is provided in the online supplement.

Pre-Registered Main Analyses

The hierarchical regression analysis revealed a nuanced pattern of findings that differed across timepoints. Results of the final models are presented in Table 3 (predicting resilience during the university transition) and Table 4 (predicting resilience during the COVID-19 pandemic).

As noted above, although the main effect for risk is entered in Block 1, main effects for both risk and protection are interpreted in Block 2. Findings indicated that the cumulative risk and protective indices were associated significantly with resilience during the university transition

[3] The protective-protective model generally is tested through a separate regression analysis that replaces the risk × protection interaction term in Block 3 with a risk × number of protective factors term. However, when a cumulative (i.e., "count") index is used, these interactions are identical, and therefore, a separate equation is not necessary. Therefore, following prior work in the field (e.g., Evans et al., 2010), the protective-protective model instead is assessed for significance after the final block is entered.

Table 4 Predicting resilience during the COVID-19 pandemic

Variable	*B*	*β*	*SE B*	*p*	95% CI
Risk *Block 2*	−1.09	−.27	.17	<.001	−1.42, −0.76
Protective *Block 2*	1.16	.27	.18	<.001	0.80, 1.51
Risk × protective *Block 3*	−0.09	−.04	.20	.651	−0.47, 0.29
Risk × protective *Block 4*	−0.15	−.06	.21	.480	−0.55, 0.26
Risk × risk *Block 4*	−0.13	−.11	.14	.384	−0.41, 0.16

($\beta = -.31$, $p \leq .001$, 95% CI [−1.40, −0.99] and $\beta = .34$, $p \leq .001$, 95% CI [1.17, 1.59], respectively). Similarly, both the cumulative risk and protective indices were associated significantly with resilience during the COVID-19 pandemic ($\beta = -.27$, $p \leq .001$, 95% CI [−1.42, −0.76] and $\beta = .27$, $p \leq .001$, 95% CI [0.80, 1.51], respectively). This pattern of findings (illustrated in Fig. 2) indicates support for the compensatory model across timepoints, suggesting that in the present sample, risk and protective factors contributed additively to resilience at both timepoints, with a greater number of risk factors decreasing resilience and a greater number of protective factors increasing resilience.

In addition, the risk × protection interaction term was associated significantly with levels of resilience in Block 3 during the university transition, $\beta = 0.10$, $p = .042$, 95% CI [0.01, 0.44], but not during the COVID-19 pandemic, $\beta = -0.04$, $p = .651$, 95% CI [−0.47, 0.29]. Simple slopes analyses indicated that higher risk level was associated with lower resilience both when an individual had a high (+1 SD) level of protective factors, $B = -0.96$, $t\,(1071) = -6.03$, $p \leq .001$, and a low level (−1 SD) of protective factors, $B = -1.40$, $t\,(1071) = -10.21$, $p \leq .001$. Further, these slopes differed significantly, $z = 2.07$, $p = .038$, such that as protective factors increased, the influence of risk level on resilience decreased. We used the Johnson-Neyman technique to determine the region of significance; this analysis indicated that an individual's risk score was no longer associated significantly with resilience ($p > .05$) when protective factors were at or above 3.80. This provides support for the risk-protective model and indicates that higher levels of protective factors, relative to lower levels of protective factors, had a greater buffering effect on the relation between risk factors and resilience during the university transition; see Fig. 3.

Neither the challenge model nor the protective-protective model was supported during the university transition, $\beta s < |.13|$, $ps \geq .090$, or the COVID-19 pandemic, $\beta s < |.11|$, $ps \geq .384$. Notably, main effects of cumulative risk and protective indices remained significant following the inclusion of the risk x protection interaction term, $ps < .001$. This indicates robust support for the compensatory model across timepoints.

We next tested whether the findings reported above remained after including relevant covariates in the model (see online supplement). When the hierarchical regression analyses were repeated with significant covariates (i.e., racial identity) included in the model, an identical pattern of findings emerged: the cumulative risk and protective indices continued to be significantly associated with resilience during the university transition and the COVID-19 pandemic, $\beta s \geq |.33|$, $ps \leq .001$. In addition, the risk × protection interaction term continued to be associated with resilience during

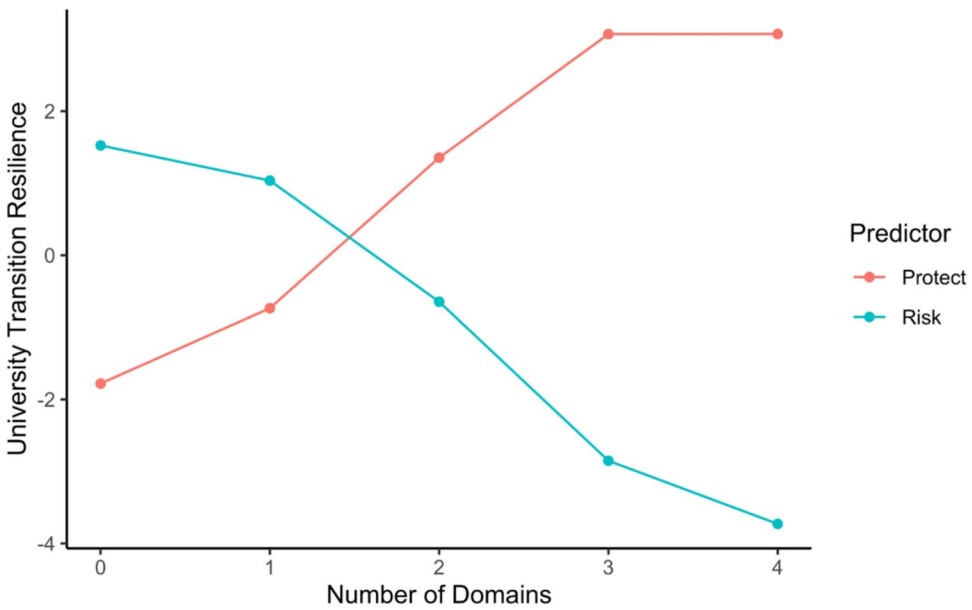

Fig. 2 Effects of risk and protective factors on predicted levels of resilience during the university transition

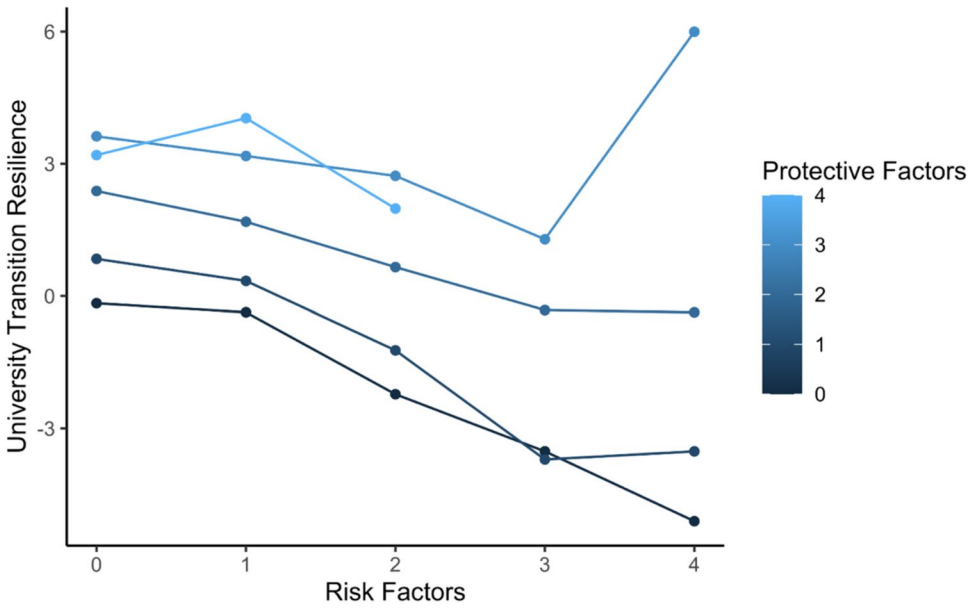

Fig. 3 Mean resilience during the university transition across number of risk factors for students with different levels of protective factors

the university transition, $\beta = .11$, $p = .027$, 95% CI [0.03, 0.45].[4]

Exploratory Post-Hoc Analyses

Although gender was not associated with resilience during the university transition ($p = .669$) or the COVID-19 pandemic ($p = .854$), given increased awareness of the importance of gender-based analyses, we considered gender as a potential moderator and conducted post hoc exploratory analyses examining the four proposed models of resilience. The interactions between gender and each of the predictors (i.e., main effects of risk and protective factors and interaction terms) were not significant in predicting resilience at either timepoint, $ps \geq .105$. In line with this finding, subgroup analyses indicated that the compensatory model held among both women and men during the university transition, $\beta s \geq |.40|$, $ps \leq .001$, and during the COVID-19 pandemic, $\beta s \geq |.33|$, $ps \leq .001$. Intriguingly, subgroup analyses also indicated that the risk-protective model existed among women, $\beta = .15$, $p = .010$, 95% CI [0.01, 0.44], but not among men, $\beta = -0.06$, $p = .619$, 95% CI [0.08, 0.56], during the university transition.

Discussion

This pre-registered work is the first to test four major models of resilience across two successive stressors during emerging adulthood. Findings bolster the compensatory model, which holds that risk and protective factors contribute additively to predict resilience, as the most well-supported model of resilience across ages, genders, and contexts. This speaks not only to the importance of mitigating risk factors but also to the central role of protective factors in promoting resilience during emerging adulthood, as the compensatory model highlights the direct and independent impact of protective factors on resilience, regardless of risk level. This is particularly critical given that many risk factors (e.g., first-generation student status) are not amendable to modification. As such, this work underscores the importance of interventions that foster protective factors to promote positive coping in times of transition.

Our findings also provide support for the risk-protective model, which posits that protective factors buffer risk factors to reduce negative outcomes. This was found during the university transition but not the pandemic. Although some prior work has found support for this model in predicting clinical outcomes and broader trajectories of well-being in youth and adults (Anyan & Hjemdal, 2016; Askeland et al., 2020; Hurd et al., 2009; McLaren & Challis, 2009; Pisarska et al., 2016), recent work in emerging adults has failed to find support for the risk-protective model (Heinze et al., 2020; Oginni et al., 2020). It has been posited that such inconsistencies may be attributable to the nature of the stressor or how it was experienced by each individual (Luthar et al., 2000; Rutter, 2012). Importantly, our results speak to these ideas by examining resilience across two different stressors within the same individuals. Notably, students reported greater psychopathology during the university transition compared to the pandemic and greater perceived stress during the pandemic compared to the university transition. These findings suggest that the nature of the stressor may influence how risk and protective

[4] A similar pattern of findings emerged when controlling for site; see online supplement.

factors operate. Increased levels of psychopathology suggest that the transition to university was a particularly vulnerable time for students, wherein protective factors could play a crucial role in mitigating distress. Indeed, the university transition, a relatively structured and expected stressor, may be particularly conducive to buffering effects via protective factors such as academic self-efficacy and social belonging. In contrast, the pandemic involved widespread yet highly individualized disruptions marked by significant variance in campus- and country-level responses. Given that students reported greater levels of perceived stress but lower levels of psychopathology during this time compared to the university transition, it is possible that the pandemic's unpredictable nature resulted in a unique constellation of adaptational challenges, wherein protective factors were less effective in buffering against distress. This is consistent with the fact that we found support for the compensatory model but not for the risk-protective model during the pandemic, given evidence that compensatory effects are stronger than buffering effects as inter-individual differences increase (Donnellan et al., 2009; Masten, 2001).

An additional explanation for these discrepant findings relates to the specific risk and protective factors used in the present study. Risk and protective factors vary in their applicability depending on age, gender, and the specific stressor being encountered (Evans et al., 2010). For instance, academic self-efficacy and belongingness at university may have been particularly powerful buffers against risk factors during the university transition, and comparatively less so during the COVID-19 pandemic, which could explain the specific support we found for the risk-protective model during the university transition.

The present work has theoretical and clinical implications. Theoretically, the four resilience models tested in the present study are not fundamentally competitive. Rather, investigating these models can clarify the nature of resilience during emerging adulthood.

Indeed, the inclusion of both cross-sectional and longitudinal analyses enables us to test whether resilience is trait-like (with factors influencing levels of resilience stably across time and contexts) and whether it is state-like (with factors manifesting differently across both time and circumstances). This approach allows us to examine how resilience patterns may change not only due to the temporal shift from cross-sectional to prospective analyses but also due to the specific contextual circumstances (such as the COVID-19 pandemic) that participants experienced during different assessment periods. Our findings support both the former and the latter. Indeed, we found that risk and protective factors had direct and independent effects on levels of resilience across timepoints, suggesting a trait-like stability to resilience. Interestingly, our results also indicate a state-like aspect to resilience, such that during some—but not all—stressors, a buffering association exists between risk and protective factors. Further supporting both trait- and state-like aspects of resilience, we found that certain indicators of resilience were stable within individuals at both timepoints (i.e., satisfaction with life; subjective happiness), whereas others were not (i.e., psychopathology; perceived stress). Broadly, our findings support a degree of stability in resilience while also demonstrating situational variability, aligning with contemporary models of resilience that recognize its dynamic nature. This nuanced understanding of resilience has the potential to inform future studies and methodologies in this area and has clinical implications: by understanding how risk and protective factors promote or impede resilience during stress, results inform the content and timing of intervention and prevention efforts. Indeed, our findings support the central role of protective factors in promoting resilience during emerging adulthood. Interventions designed to enhance protective factors in the context of risk factors may offer the strongest potential for supporting resilience (Fergus, and Zimmerman, 2005; Zimmerman, et al., 2013), and importantly, the protective factors examined in the present work are highly modifiable through targeted interventions that could be delivered within the university setting (Houston et al., 2017; Steinhardt & Dolbier, 2008). Indeed, there is robust evidence that programs aimed at bolstering academic self-efficacy, enhancing social support, and fostering a sense of belongingness can improve student well-being and mental health outcomes. For example, Walton and Cohen (2011) documented that a brief intervention to enhance belongingness at university improved minority students' self-reported health, well-being, and academic performance. Thus, our findings underscore the potential for campus-based initiatives that specifically aim to enhance these modifiable protective factors among vulnerable student populations.

Our findings should be interpreted in the context of several study limitations. First, the present work was conducted in an international sample of university students. Although the risk for psychopathology and decreased well-being among university students has been well-substantiated (Auerbach et al., 2018), individuals who attend university tend to share certain qualities, such as more privileged socioeconomic backgrounds, that may differ from general community samples of emerging adults (Hanel & Vione, 2016). As a result, our findings may not generalize to emerging adults more broadly, and additional research is needed to investigate longitudinal trajectories of resilience in community samples of emerging adults, accounting for factors such as income, education, and socioeconomic status. Relatedly, our sample was drawn from universities situated in Western, largely individualistic cultures (Canada, the United Kingdom, and the United States). As a result, the findings may not

generalize to individuals from other countries and contexts such as more collectivistic cultures wherein social norms, protective assets, and support systems may shape risk and resilience processes differently. Future research should aim to replicate these findings in more diverse cultural contexts to better understand the universality versus cultural specificity of the observed associations. Further, our sample had minimal representation of Latinx/e and Black participants; thus, future work also would also be strengthened by more diverse samples. Next, cumulative indices of risk and protective factors included in the current study were derived empirically from the literature examining risk and protective factors in emerging adulthood. However, it is impossible to rule out the possibility that other indicators may have revealed different trends. Thus, although the results of the current study are broadly in line with previous research that has found support for the compensatory and risk-protective models across the lifespan, future research incorporating a greater diversity of risk and protective factors may further extend this literature. Finally, although our dichotomization of risk and protective factors was grounded in prior resilience and stress research (Evans et al., 2010; Hollister-Wagner et al., 2001; Juster et al., 2010) and was necessary given some variables were inherently dichotomous (e.g., first-generation student status), a dichotomous approach may reduce statistical power and obscure potential gradations in the observed effects. Future research would benefit from examining risk and protective factors continuously to capture more nuanced associations and maximize analytic precision.

Motivated by recent evidence for the vulnerable nature of emerging adulthood, this pre-registered work is the first to test four primary models of resilience during emerging adulthood. Following an international sample across two ubiquitous, naturalistic, and successive stressors, these results advance research on well-being in this cohort and have the potential to guide future theory development. Further, findings demonstrate that protective factors enhance resilience, regardless of risk. As such, the present results highlight the dynamic nature of resilience and underscore the opportunity to enhance resilience in emerging adulthood through the promotion of protective factors.

Acknowledgements We thank the individuals who participated in this study and the research assistants who supported data collection.

Additional Information

Funding This research was supported by a Social Sciences and Humanities Research Council (SSHRC) Vanier Canada Graduate Fellowship to EJ; a SSHRC Grant 430–2017-00408 to JL; and a Michael Smith Foundation for Health Research Scholar Award 17713 to JL. Beyond this funding, the authors have no competing interests to declare that are relevant to the content of this article.

Competing interests The authors declare no competing interests.

Availability of Data and Material The data that support the findings of this study are available from the EMERGE Project, but restrictions apply to the online availability of these data. Specifically, data were collected as part of an international multi-site collaboration and so are not publicly available. The data are, however, available from the authors upon reasonable request and with the permission of site leads.

Code Availability Not applicable.

Authors' Contributions EJ: formal analysis of data, writing original draft, reviewing and editing the draft; TJ: writing original draft, reviewing and editing the draft; SGI: reviewing and editing the draft; GY: reviewing and editing the draft; IBM: reviewing and editing the draft; LBA: reviewing and editing the draft; JLB: reviewing and editing the draft; BB: reviewing and editing the draft; SRH: reviewing and editing the draft; SK: reviewing and editing the draft; LM: reviewing and editing the draft; DPM: reviewing and editing the draft; RN: reviewing and editing the draft; AO: reviewing and editing the draft: RBB: reviewing and editing the draft; GPS: reviewing and editing the draft; SMV: reviewing and editing the draft; JG: supervision, reviewing and editing the draft; JL: supervision, reviewing and editing the draft.

Ethics Approval This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethics Committees of the University of British Columbia (BREB #H19-01559), University College London (IRB #12,673/001), the University of Colorado Boulder (IRB #18–0483), and Temple University (IRB #26,117).

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Consent for Publication Not applicable.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s42761-025-00322-z.

References

Algorta, G. P., Youngstrom, E. A., Phelps, J., Jenkins, M. M., Youngstrom, J. K., & Findling, R. L. (2013). An inexpensive family index of risk for mood issues improves identification of pediatric bipolar disorder. *Psychological Assessment, 25*(1), 12–22.

American Psychiatric Association. (2013). *The DSM-5 Self-Rated Level 1 Cross-Cutting Symptom Measure – Adult*. https://www.psychiatry.org/getmedia/e0b4b299-95b3-407b-b8c2-caa871ca218d/APA-DSM5TR-Level1MeasureAdult.pdf.

Anastasiades, M. H., Kapoor, S., Wootten, J., & Lamis, D. A. (2017). Perceived stress, depressive symptoms, and suicidal ideation in undergraduate women with varying levels of mindfulness. *Archives of Women's Mental Health, 20*(1), 129–138.

Anyan, F., & Hjemdal, O. (2016). Adolescent stress and symptoms of anxiety and depression: Resilience explains and differentiates the relationships. *Journal of Affective Disorders, 203*, 213–220.

Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist, 55*(5), 469–480.

Arnett, J. J. (2007). Emerging adulthood: What is it, and what is it good for? *Child Development Perspectives, 1*(2), 68–73.

Askeland, K. G., Bøe, T., Breivik, K., La Greca, A. M., Sivertsen, B., & Hysing, M. (2020). Life events and adolescent depressive symptoms: Protective factors associated with resilience. *PLoS One,15*(6), Article e0234109.

Atkinson, L., Beitchman, J., Gonzalez, A., Young, A., Wilson, B., Escobar, M., et al. (2015). Cumulative risk, cumulative outcome: A 20-year longitudinal study. *PloS One, 10*(6), e0127650.

Auerbach, R. P., Alonso, J., Axinn, W. G., Cuijpers, P., Ebert, D. D., Green, J. G., et al. (2016). Mental disorders among college students in the World Health Organization world mental health surveys. *Psychological Medicine, 46*(14), 2955–2970.

Auerbach, R. P., Mortier, P., Bruffaerts, R., Alonso, J., Benjet, C., Cuijpers, P., Demyttenaere, K., Ebert, D. D., Green, J. G., Hasking, P., Murray, E., Nock, M. K., Pinder-Amaker, S., Sampson, N. A., Stein, D. J., Vilagut, G., Zaslavsky, A. M., & Kessler, R. C. (2018). WHO world mental health surveys international college student project: Prevalence and distribution of mental disorders. *Journal of Abnormal Psychology, 127*(7), 623–638.

Bauer, D. J., & Curran, P. J. (2005). Probing interactions in fixed and multilevel regression: Inferential and graphical techniques. *Multivariate Behavioral Research, 40*(3), 373–400.

Bayram, N., & Bilgel, N. (2008). The prevalence and socio-demographic correlations of depression, anxiety and stress among a group of university students. *Social Psychiatry and Psychiatric Epidemiology, 43*(8), 667–672.

Bonanno, G. A. (2004). Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after extremely aversive events? *American Psychologist, 59*(1), 20–28.

Brett, C. E., Mathieson, M. L., & Rowley, A. M. (2022). Determinants of wellbeing in university students: The role of residential status, stress, loneliness, resilience, and sense of coherence. *Current Psychology*. https://doi.org/10.1007/s12144-022-03125-8

Bronfenbrenner, U. (1979). *The ecology of human development*. Harvard University Press.

Browning, M. H. E. M., Larson, L. R., Sharaievska, I., Rigolon, A., McAnirlin, O., Mullenbach, L., Cloutier, S., Vu, T. M., Thomsen, J., Reigner, N., Covelli Metcalf, E., D'Antonio, A., Helbich, M., Bratman, G. N., & Olvera Alvarez, H. (2021). Psychological impacts from COVID-19 among university students: Risk factors across seven states in the United States. *PLoS One,16*(1), Article e0245327.

Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS scales. *Journal of Personality and Social Psychology, 67*, 319–333.

Chemers, M. M., Hu, L.-T., & Garcia, B. F. (2001). Academic self-efficacy and first year college student performance and adjustment. *Journal of Educational Psychology, 93*(1), 55–64.

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior, 24*(4), 385–396.

Corral-Frías, N. S., Nadel, L., Fellous, J. M., & Jacobs, W. J. (2016). Behavioral and self-reported sensitivity to reward are linked to stress-related differences in positive affect. *Psychoneuroendocrinology, 66*, 205–213.

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment, 49*(1), 71–75.

Donnellan, M. B., Conger, K. J., McAdams, K. K., & Neppl, T. K. (2009). Personal characteristics and resilience to economic hardship and its consequences: Conceptual issues and empirical illustrations. *Journal of Personality, 77*(6), 1645–1676.

Dubow, E. F., & Luster, T. (1990). Adjustment of children born to teenage mothers: The contribution of risk and protective factors. *Journal of Marriage and the Family, 52*(2), 393–404.

Ehrenreich, S. E., Beron, K. J., & Underwood, M. K. (2016). Social and physical aggression trajectories from childhood through late adolescence: Predictors of psychosocial maladjustment at age 18. *Developmental Psychology, 52*(3), 457.

Elder, J. G. (1985). *Life course dynamics: Trajectories and transitions 1968–1980*. Cornell University Press.

Ensminger, M. E., Hanson, S. G., Riley, A. W., & Juon, H. S. (2003). Maternal psychological distress: Adult sons' and daughters' mental health and educational attainment. *Journal of the American Academy of Child and Adolescent Psychiatry,42*(9), 1108–1115.

Evans, W. P., Marsh, S. C., & Weigel, D. J. (2010). Promoting adolescent sense of coherence: Testing models of risk, protection, and resiliency. *Journal of Community & Applied Social Psychology,20*(1), 30–43.

Fergus, S., & Zimmerman, M. A. (2005). Adolescent resilience: A framework for understanding healthy development in the face of risk. *Annual Review of Public Health,26*(1), 399–419.

Fromme, K., Katz, E. C., & Rivet, K. (1997). Outcome expectancies and risk-taking behavior. *Cognitive Therapy and Research, 21*, 421–442.

Garmezy, N., Masten, A. S., & Tellegen, A. (1984). The study of stress and competence in children: A building block for developmental psychopathology. *Child Development, 55*(1), 97–111.

Gaumer Erickson, A. S. & Noonan, P. M. (2018). Self-efficacy formative questionnaire. In *The skills that matter: Teaching interpersonal and intrapersonal competencies in any classroom* (pp. 175–176). Thousand Oaks, CA: Corwin.

Goldstein, A. L., Faulkner, B., & Wekerle, C. (2013). The relationship among internal resilience, smoking, alcohol use, and depression symptoms in emerging adults transitioning out of child welfare. *Child Abuse & Neglect,37*(1), 22–32.

Gopalan, M., & Brady, S. T. (2020). College students' sense of belonging: A national perspective. *Educational Researcher, 49*(2), 134–137.

Gros, D. F., Gros, K. S., & Simms, L. J. (2010). Relations between anxiety symptoms and relational aggression and victimization in emerging adults. *Cognitive Therapy and Research, 34*(2), 134–143.

Grøtan, K., Sund, E. R., & Bjerkeset, O. (2019). Mental health, academic self-efficacy and study progress among college students–The shot study, Norway. *Frontiers in Psychology, 10*, Article 45.

Gruber, J., Hinshaw, S. P., Clark, L. A., Rottenberg, J., & Prinstein, M. J. (2023). Young adult mental health beyond the COVID-19 era: Can enlightened policy promote long-term change? *Policy Insights from the Behavioral and Brain Sciences, 10*(1), 75–82.

Gruber, J., Prinstein, M. J., Clark, L. A., Rottenberg, J., Abramowitz, J. S., Albano, A. M., Aldao, A., Borelli, J. L., Chung, T., Davila, J., Forbes, E. E., Gee, D. G., Hall, G. C. N., Hallion, L. S., Hinshaw, S. P., Hofmann, S. G., Hollon, S. D., Joormann, J., Kazdin, A. E., & Weinstock, L. M. (2021). Mental health and clinical psychological science in the time of COVID-19: Challenges, opportunities, and a call to action. *American Psychologist, 76*(3), 409.

Hanel, P. H., & Vione, K. C. (2016). Do student samples provide an accurate estimate of the general public? *PLoS One,11*(12), Article e0168354.

Harvey, A. G., Dong, L., Hein, K., Yu, S. H., Martinez, A. J., Gumport, N. B., Smith, F. L., Chapman, A., Lisman, M., Mirzadegan, I. A., Mullin, A. C., Fine, E., Dolsen, E. A., Gasperetti, C. E., Bukosky, J., Alvarado-Martinez, C. G., Kilbourne, A. M., Rabe-Hesketh, S., & Buysse, D. J. (2021). A randomized controlled trial of the transdiagnostic intervention for sleep and circadian dysfunction (TranS-C) to improve serious mental illness outcomes in a community setting. *Journal of Consulting and Clinical Psychology, 89*(6), 537–550.

Hayes, T., & Usami, S. (2020). Factor score regression in the presence of correlated unique factors. *Educational and Psychological Measurement, 80*(1), 5–40.

Heinze, J. E., Hsieh, H. F., Aiyer, S. M., Buu, A., & Zimmerman, M. A. (2020). Adolescent family conflict as a predictor of relationship quality in emerging adulthood. *Family Relations,69*(5), 996–1011.

Hollister-Wagner, G. H., Foshee, V. A., & Jackson, C. (2001). Adolescent aggression: Models of resiliency. *Journal of Applied Social Psychology, 31*(3), 445–466.

Hoshino, T., & Bentler, P. M. (2013). Bias in factor score regression and a simple solution. In A. R. de Leon & K. C. Chough (Eds.), *Analysis of mixed data: Methods & applications* (pp. 43–61). Chapman & Hall.

House, L. A., Neal, C., & Kolb, J. (2020). Supporting the mental health needs of first generation college students. *Journal of College Student Psychotherapy, 34*(2), 157–167.

Houston, J. B., First, J., Spialek, M. L., Sorenson, M. E., Mills-Sandoval, T., Lockett, M., First, N. L., Nitiéma, P., Allen, S. F., & Pfefferbaum, B. (2017). Randomized controlled trial of the resilience and coping intervention (RCI) with undergraduate university students. *Journal of American College Health, 65*(1), 1–9.

Huesmann, L. R., Dubow, E. F., & Boxer, P. (2009). Continuity of aggression from childhood to early adulthood as a predictor of life outcomes: Implications for the adolescent-limited and life-course-persistent models. *Aggressive Behavior: Official Journal of the International Society for Research on Aggression, 35*(2), 136–149.

Hurd, N. M., Zimmerman, M. A., & Xue, Y. (2009). Negative adult influences and the protective effects of role models: A study with urban adolescents. *Journal of Youth and Adolescence, 38*(6), 777–789.

Ibonie, S. G., Young, G., Ploe, M. L., Mauss, I. B., Alloy, L. B., Borelli, J. L., et al. (2025). Bipolar spectrum risk and social network dimensions in emerging adults: Two social sides? *Journal of Social and Clinical Psychology, 44*(1), 1–28.

Jenkins, S. R., Belanger, A., Connally, M. L., & Duron, K. M. (2013). First-generation undergraduate students' social support, depression, and life satisfaction. *Journal of College Counseling, 16*(2), 129–142.

Juster, R. P., McEwen, B. S., & Lupien, S. J. (2010). Allostatic load biomarkers of chronic stress and impact on health and cognition. *Neuroscience and Biobehavioral Reviews, 35*(1), 2–16.

Kline, R. B. (1998). *Structural equation modeling*. Guilford.

Leary, K. A., & DeRosier, M. E. (2012). Factors promoting positive adaptation and resilience during the transition to college. *Psychology,3*, 1215–1222.

Luthar, S. S., Cicchetti, D., & Becker, B. (2000). The construct of resilience: A critical evaluation and guidelines for future work. *Child Development, 71*(3), 543–562.

Luthar, S. S. (2006). Resilience in development: A synthesis of research across five decades. In D. Cicchetti & D. J. Cohen (Eds.), *Developmental psychopathology: Risk, disorder, and adaptation* (pp. 739–795). John Wiley & Sons Inc.

Lyubomirsky, S., & Lepper, H. S. (1999). A measure of subjective happiness: Preliminary reliability and construct validation. *Social Indicators Research, 46*, 137–155.

Masten, A. S. (2001). Ordinary magic. Resilience processes in development. *American Psychologist,56*(3), 227–238.

Masten, A. S., Best, K., & Garmezy, N. (1990). Resilience and development: Contributions from the study of children who overcome adversity. *Development and Psychopathology, 2*(4), 425–444.

Masten, A. S., Lucke, C. M., Nelson, K. M., & Stallworthy, I. C. (2021). Resilience in development and psychopathology: Multisystem perspectives. *Annual Review of Clinical Psychology, 17*, 521–549.

Masten, A. S., Obradović, J., & Burt, K. B. (2006). Resilience in emerging adulthood: Developmental perspectives on continuity and transformation. In J. J. Arnett & J. L. Tanner (Eds.), *Emerging adults in America: Coming of age in the 21st century* (pp. 173–190). American Psychological Association.

McLaren, S., & Challis, C. (2009). Resilience among men farmers: The protective roles of social support and sense of belonging in the depression-suicidal ideation relation. *Death Studies, 33*(3), 262–276.

Mitchell, J. M., & Abraham, K. M. (2018). Parental mental illness and the transition to college: Coping, psychological adjustment, and parent–child relationships. *Journal of Child and Family Studies, 27*, 2966–2977.

Modecki, K. L. (2016). Do risks matter? Variable and person-centered approaches to adolescents' problem behavior. *Journal of Applied Developmental Psychology,42*, 8–20.

Oginni, O. A., Mapayi, B. M., Afolabi, O. T., Obiajunwa, C., & Oloniniyi, I. O. (2020). Internalized homophobia, coping, and quality of life among Nigerian gay and bisexual men. *Journal of Homosexuality, 67*(10), 1447–1470.

Ostaszewski, K., & Zimmerman, M. A. (2006). The effects of cumulative risks and promotive factors on urban adolescent alcohol and other drug use: A longitudinal study of resiliency. *American Journal of Community Psychology,38*(3–4), 251–262.

Pisarska, A., Eisman, A., Ostaszewski, K., & Zimmerman, M. A. (2016). Alcohol and cigarette use among Warsaw adolescents: Factors associated with risk and resilience. *Substance Use & Misuse,51*(10), 1283–1296.

R Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/

Rahat, E., & Ilhan, T. (2016). Coping styles, social support, relational self-construal, and resilience in predicting students' adjustment to university life. *Educational Sciences: Theory & Practice, 16*(1), 187–208.

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software,48*, 1–36. https://doi.org/10.18637/jss.v048.i02

Rutter, M. (1985). Resilience in the face of adversity. Protective factors and resistance to psychiatric disorder. *The British Journal of Psychiatry, 147*, 598–611.

Rutter, M. (2012). Resilience as a dynamic concept. *Development and Psychopathology, 24*(2), 335–344.

Seery, M. D. (2011). Resilience: A silver lining to experiencing adverse life events? *Current Directions in Psychological Science, 20*(6), 390–394.

Southwick, S. M., Bonanno, G. A., Masten, A. S., Panter-Brick, C., & Yehuda, R. (2014). Resilience definitions, theory, and challenges: Interdisciplinary perspectives. *European Journal of Psychotraumatology*. https://doi.org/10.3402/ejpt.v5.25338

Steinhardt, M., & Dolbier, C. (2008). Evaluation of a resilience intervention to enhance coping strategies and protective factors and decrease symptomatology. *Journal of American College Health, 56*(4), 445–453.

Suhlmann, M., Sassenberg, K., Nagengast, B., & Trautwein, U. (2018). Belonging mediates effects of student-university fit on well-being, motivation, and dropout intention. *Social Psychology, 49*(1), 16–28.

Taubitz, L. E., Pedersen, W. S., & Larson, C. L. (2015). BAS reward responsiveness: A unique predictor of positive psychological functioning. *Personality and Individual Differences, 80*, 107–112.

Taylor, Z. E., Doane, L. D., & Eisenberg, N. (2014). Transitioning from high school to college: Relations of social support, ego-resiliency, and maladjustment during emerging adulthood. *Emerging Adulthood, 2*(2), 105–115.

Troy, A. S., Willroth, E. C., Shallcross, A. J., Giuliani, N. R., Gross, J. J., & Mauss, I. B. (2023). Psychological resilience: An affect-regulation framework. *Annual Review of Psychology, 74*, 547–576.

Walton, G. M., & Cohen, G. L. (2007). A question of belonging: Race, social fit, and achievement. *Journal of Personality and Social Psychology, 92*(1), 82–96.

Walton, G. M., & Cohen, G. L. (2011). A brief social-belonging intervention improves academic and health outcomes of minority students. *Science, 331*(6023), 1447–1451.

Xia, Y., & Ma, Z. (2020). Social integration, perceived stress, locus of control, and psychological wellbeing among Chinese emerging adult migrants: A conditional process analysis. *Journal of Affective Disorders, 267*, 9–16.

Zimmerman, M. A., Stoddard, S. A., Eisman, A. B., Caldwell, C. H., Aiyer, S. M., & Miller, A. (2013). Adolescent resilience: Promotive factors that inform prevention. *Child Development Perspectives, 7*(4), 215–220.