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Parents' adjustment following the death of their child: Resilience is multidimensional and differs across outcomes examined

Frank J. Infurna and **Suniya S. Luthar**
Arizona State University, Tempe, USA

Abstract

We examine whether the previously reported commonness of resilience to significant adversity extends to parents' death of a child. To examine our research questions, we apply growth mixture models to longitudinal data from 461 parents in the HILDA study who had experienced child loss. The proportion of parents manifesting resilience were 44%, 56%, 21%, 32%, and 16% for life satisfaction, negative affect, positive affect, general health, and physical functioning, respectively. Only 5% were resilient across all five indices, whereas 28% did not show a resilient trajectory across all outcomes. Social connectedness, anticipating comfort when distressed, and everyday role functioning were the strongest predictors of resilient adaptation. Findings underscore that resilience is not a unidimensional construct.

Keywords

Resilience; Child Loss; HILDA; Subjective Well-Being; Major Life Stressors; Bereavement

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Our primary aim is to appraise reports that resilience to significant adversity is commonplace. A large corpus of studies has shown that trajectories of stable, healthy psychological functioning are the modal response among individuals confronted with a wide range of adversities, including military deployment, heart attack, and unemployment (Bonanno, 2004; Bonanno et al., 2015). More recently, however, the commonness of resilience has been challenged, with suggestions that this could partly be an artifact of data analytic and measurement choices (Infurna & Luthar, 2016; in press). We examine these opposing perspectives in the context of parents' loss of a child, an event that is traumatic for most.

We also address suggestions that resilience implies "across-the-board" doing well despite adversity, as it has been long established that the likelihood of resilience is dependent on the outcome of interest; in other words, resilience is multidimensional in nature (see Luthar, Doernberger, & Zigler, 1993). In the context of child loss, it has recently been shown that

Address correspondence regarding this manuscript to: Frank J. Infurna, Arizona State University, Department of Psychology, 950 S. McAllister Ave., Tempe, AZ 85287, Frank.Infurna@asu.edu.

most parents are resilient based on exhibiting stable, low levels of depressive symptoms (Maccullum et al., 2015). However, this broad claim is questionable as it is based on a single measure of adjustment, with recent research showing cross-domain variability across outcomes, indicating that resilience in a specific outcome co-exists with declines in others (Infurna & Luthar, in press). Various negative sequelae can and have been shown to occur among bereaved parents including low levels of well-being and diverse symptoms of distress (Rogers et al., 2008; Wijngaards-de Meij et al., 2005).

Finally, we examine salient vulnerability and protective factors that might exacerbate or mitigate the ill-effects of child loss. Our interest is chiefly in factors that might, if found to be significant, be harnessed in future preventive interventions, such as discrete aspects of everyday social relationships.

Resilience to Child Loss

Research evidence to date is mixed regarding the typical parental response to the death of a child. Initial research utilized cross-sectional comparisons of bereaved parents to those who had not experienced child loss. Results indicated that as compared to a matched comparison group who did not experience child loss, child-bereaved parents were more likely to report poorer psychological well-being and higher levels of depressive symptoms, worry and anxiety, up to 4–18 years following child loss (Floyd et al., 2013; Lehman et al., 1987; Rogers et al., 2008). Longitudinal research by Wijngaards-de Meij and colleagues (2005, 2008) followed child bereaved parents over 3 assessments across 20 months of time, with findings showing that grief and depressive symptoms persisted, but slightly declined following child loss.

By contrast, a recent study by Maccallum and colleagues (2015) utilized prospective longitudinal data to examine trajectories of depressive symptoms before and after child loss, and showed that resilience (low depressive symptoms) was the typical trajectory (64%). Additional observed trajectories were chronic high (11%), improvement (11%), and grief (14%). This study substantively advanced the field because it had one assessment of pre-loss data; showed considerable heterogeneity in individuals’ adjustment over time; and used a known class procedure to compare experiences of child loss to spousal loss. However, there were notable limitations that we build upon here, including the use of a single indicator that precludes knowing whether resilience in one outcome implies across-the-board resilience across other salient outcomes; limited pre-loss data (inhibiting examination of pre-loss changes); and restrictive assumptions underlying the longitudinal model of change.

The resilience literature in adulthood and old age considers resilience to be a unidimensional reaction to adversity (Bonanno, 2004; Bonanno et al., 2015). This conclusion has been drawn from research studies that have typically included the use of a single outcome and from this, broad statements regarding overall resilience have been made. For example, Galatzer-Levy and Bonanno (2014) examined trajectories of depressive symptoms following heart trouble and found that 68% of the sample exhibited a resilient trajectory; they concluded that their study provided population-based estimates of the proportion of individuals who follow distinct trajectories. However, we would argue that it is erroneous to extrapolate that resilience in one measured outcome implies that resilience will be manifest in other pertinent outcomes, especially if other outcomes are not examined (e.g., resilience found in depressive symptoms or life satisfaction may not correspond to resilience in physical health and well-being; Infurna & Luthar, in press). This underscores the need for researchers to simultaneously examine multiple pertinent outcomes in operationalizing the construct of resilience.

The multidimensional nature of resilience has long been acknowledged in the developmental literature, but has rarely been considered explicitly in studies with adults. In an early study of stress-exposed inner-city youth, Luthar and colleagues (1993) demonstrated that excellent functioning in some critical domains, such as academic achievement, often co-existed with major deficits in other important areas, including peer acceptance and symptoms of distress. In a study of adults who suffered spinal cord injuries, deRoon-Cassini and colleagues (2010) found that resilience was the modal trajectory in both PTSD and depressive symptoms. Mancini and colleagues (2015) observed that resilience was modal to an on-campus shooting in both anxiety and depressive symptoms, with concordance across these. Going beyond internalizing symptoms, however, Infurna and Luthar (in press) demonstrated varying rates of resilience among adults who experienced spousal loss, as the likelihood of exhibiting resilience was dependent on the outcome considered. On life satisfaction, negative and positive affect, general health and physical functioning, respectively, proportions of individuals in resilient trajectories were 66%, 19%, 26%, 37%, and 28%. When considered collectively, only 8% showed across-the-board resilience, whereas 20% showed a *non-resilient* trajectory across all five indicators. The Infurna and Luthar (in press) study was instrumental in demonstrating that adults' resilience is not uniform across outcomes, with resilience in one specific domain clearly co-existing with deficits in others.

Applying this multidimensional approach in studying child bereavement, we would expect still fewer people showing across-the-board resilience given the extreme nature of this loss. Thus, we examined resilient trajectories across three aspects of subjective well-being and two of physical health. The former spanned both cognitive-evaluative (life satisfaction) and affective components (positive and negative affect), and the latter included general health and physical functioning. All these outcomes have shown to be sensitive to adversity experienced and at the same time, are conceptually independent of one another (e.g., Diener, 1984; Helzer & Jayawickreme, 2015 Infurna & Luthar, in press). Furthermore, each outcome provides distinct information that adds up to a more comprehensive picture of human resilience than simply the use of a single outcome, such as life satisfaction or depressive symptoms.

Vulnerability and Protective Factors

A second broad aim in this study was to identify vulnerability and protective factors reliably associated with resilient adaptation, focusing not just on demographic indices but on modifiable risk-modifiers, with an eye toward informing future interventions (Luthar, Crossman, & Small, 2015). With regard to demographics, younger bereaved parents are likely to be more affected following child loss (Keesee et al., 2008), due to differences in coping strategies (Aldwin et al., 1996). Women typically report poorer adjustment to child loss, reporting higher levels of depression and grief (Wijngaards-de Meij et al., 2005, 2008). Education has been protective against elevated levels of grief and depression following child loss (Wijngaards-de Meij et al., 2005), likely due to education being associated with greater psychosocial resources and use of adaptive and compensatory strategies (Adler et al., 1994; Infurna et al., 2011; Lachman & Weaver, 1998).

With regard to risk-modifiers potentially amenable to external interventions, we examine the contributions of three distinct indices. Close relationships are long acknowledged to be critical for resilience (Stroebe & Schut, 2010), and we examine anticipation of *reliable comfort* when distressed, shown to be strongly associated with better well-being in adults under stress (Luthar & Ciciolla, 2015). Mutually supportive relationships in one's social network and community settings can promote more outcomes that are positive, especially in the context of adversity (see Antonucci, Arouch, & Birditt, 2013). Bereavement inevitably interferes with everyday routines and functioning; yet, there can be great protective potential if individuals are able to remain somewhat *connected to their social circles*, and *continue major life routines* (Infurna & Luthar, in press; Stroebe et al., 2005).

The Present Study

In summary, we extend existing research on child bereavement by considering long-term change before and after child loss across five conceptually important adjustment indices. Whereas many individuals may seem resilient based on a single indicator (e.g., global life satisfaction), we expect that fewer will demonstrate resilience on negative and positive affective indices as well as health indicators, and a small minority of individuals will demonstrate resilience across all five outcomes. We also examine vulnerability and protective factors associated with resilience, seeking to illuminate the strongest unique associations, with resilient adaptation, for anticipating reliable comfort, social connectedness, and role functioning.

Methods

We examined our research questions using data from 13 annual waves (2001 – 2013) of the Household Income and Labour Dynamics of Australia Study (HILDA). Comprehensive information about the design, participants, variables, and assessment procedures in the study are reported in Dyrenforth, Kashy, Donnellan, & Lucas (2010); Watson, (2010). A brief overview of details relevant to the present analysis is given below.

Participants and Procedure

The HILDA is a nationally representative annual panel study of private households and their inhabitants initiated in 2001 that includes residents of Australia. Within a household, all persons aged 15 and over were invited to participate. Data are collected annually via a combination of face-to-face and telephone interviews and self-completed questionnaires.

For the present study, we included 461 participants who experienced child loss over the course of the study. At the time of child loss, participants were, on average, 54.39 years of age (*SD* = 20.19, range 16 to 93), 60% were women, 41% attained at least a high school education, and 52% were married or in a de facto relationship.

Measures

Child loss—At each wave, participants were asked whether they had experienced the death of a child in the previous year. We included those participants who reported losing a child over the course of the study.

Life satisfaction—Participants' reported on their life satisfaction annually, answering the question "How satisfied are you with your life, all things considered?" using a 0 (*totally unsatisfied*) to 10 (*totally satisfied*) rating scale. This item has been used widely in psychological research (see Fujita & Diener, 2005; Lucas et al., 2004).

Positive and negative affect—Positive and negative affect were assessed at each wave using questions starting with the stem "How much of the time during the past 4 weeks…" and answered on a scale from 1 (*all of the time*) to 6 (*none of the time*) (see Anusic, Yap, & Lucas, 2014). *Negative affect* items were "Have you been a nervous person?", "Have you felt so down in the dumps nothing could cheer you up?", "Have you felt down?", "Did you feel worn out?", and "Did you feel tired?". *Positive affect* items were "Did you feel full of life?", "Have you felt calm and peaceful?", "Did you have a lot of energy?" and "Have you been a happy person?". Items for negative and positive affect were averaged with higher scores for each indicating more frequent experience of affect. α's ranged from .81 to .86 at each wave for negative affect and α's ranged from .85 to .90 at each wave for positive affect.

General health—General health was measured using the subscale of the Short Form Survey (SF-36) that consists of 5 items, answered on a scale from 1 to 5. Specific items asked whether participants "got sick a little easier than other people", "were as healthy as anybody they knew", "expected their health to get worse", "overall health", and "health rated as compared to a year ago". Following standard scoring procedures (see Ware, Kosinski, & Keller, 1994), general health was standardized using the Australian normed population averages and standard deviations, with higher scores indicating better general health.

Physical functioning—Physical functioning is a subscale of the SF-36 that consists of 10 items asking participants whether during the past 4 weeks their health limits them across various activities, answered on a scale, "yes, limited a lot", "yes, limited a little", and "no, not limited at all". Specific items asked whether participants' health limited them in "vigorous activities" and "moderate activities", and difficulty with the ability to "lift, carry groceries", "climb several flights of stairs", "climb one flight of stairs", "bend, kneel", "walk a mile", "walk several blocks", "walk one block", "bathe, dress". Following standard score procedures (see Ware et al., 1994), physical functioning was standardized using the Australian normed population averages and standard deviations, with higher scores indicating better physical functioning.

Vulnerability and protective factors—*Reliable comfort* was measured with four items answered on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*) and averaged, with higher levels being indicative of stronger conviction of forthcoming comfort ($M = 5.03$, $SD = 1.53$, range 1 to 7). Specific items asked participants whether they had "anyone to confide in", "anyone to lean on in times of trouble", "need help from other people but couldn't get it" and whether "people visited them regularly". α's ranged from .69 to .78 from each wave.

Social connectedness is a subscale of the SF-36 that consists of two items asking participants whether during the past 4 weeks, how much of the time has your physical health or emotional problems interfered with "your social activities (like visiting friends, relatives, etc)" and "normal social activities with family, friends, neighbours, or groups", answered on a scale, "All of the time" to "None of the time". Following standard score procedures (see Ware et al., 1994), social connectedness was standardized using the Australian normed population averages and standard deviations, with higher scores indicating better social connectedness ($M = 64.70$, $SD = 29.93$, range 0 to 100).

Everyday role-functioning was measured by a subscale of the SF-36 that consists of three items asking participants whether during the past 4 weeks, have you had any of the following problems with your work or other regular daily activities as a result of any emotional problems (such as feeling depressed or anxious), "cut down the amount of time you spent on work", "accomplished less than you would like", and "didn't do work or other activities as carefully as usual", answered on a scale, "yes", and "no". Following standard score procedures (see Ware et al., 1994), role-emotional functioning was standardized using the Australian normed population averages and standard deviations, with higher scores indicating better role-emotional functioning ($M = 63.30$, $SD = 41.53$, range 0 to 100). Each variable was assessed annually and we used the assessment at the year of the reported child loss. Acknowledging that these resources may also change as a function of child loss, note that we also analyzed the data using pre- and post-assessments of each resource, and findings were substantively similar.

Statistical Analysis

We used growth mixture modeling (GMM) to examine whether there were distinct classes of individuals in how life satisfaction, positive and negative affect, general health, and physical functioning changed before and after child loss. GMM combines latent growth curve and mixture models and simultaneously estimates trajectories of change, and provides the opportunity to observe sub-groups of individuals with distinct multivariate normal distributions (for discussion, see Grimm & Ram, 2009; Muthén, 2004; Ram & Grimm, 2009). A longitudinal model of change needs to first be established to allow for GMM to subsequently identify distinct sub-groups or classes underlying the sample. To do so, each individual's time series must be realigned to year of child loss.

We used all observations between 5 years prior to and 5 years following child loss (i.e., participants could have provided up to 11 observations) for the GMM analyses conducted for this report. This was done to ensure a long enough time interval to track change before and after child loss and ensure enough statistical power to detect between-person differences (Diallo & Morin, 2015). We based our use of 11 observations from simulation and empirical studies that have shown that the inclusion of more longitudinal observations increases statistical power to detect between-person differences in longitudinal change in the outcome of interest (Hertzog et al., 2008; Rast & Hofer, 2014). In a previous study, Maccullum and colleagues (2015) had a larger sample size ($n = 2{,}512$) and used 4 total available observations, when a longer time interval was possible given the biennial assessments of the Health and Retirement Study. However, in our study, we have a smaller sample of individuals who experienced child loss ($n = 461$) and it is known that when researchers are limited by sample size, increasing the number of observations increases the statistical power to detect between-person differences in change (see Hertzog et al., 2008; Rast & Hofer, 2014). We acknowledge that these simulation and empirical studies focused on linear and quadratic patterns of change, but these principles of reliability to detect between-person differences in change increasing with observations transfers to other forms of longitudinal model of change, such as multi-phase models and GMM that we implement in this study (see Diallo et al., 2016). The average number of observations were considered in this study was 7.81 for life satisfaction ($SD = 2.36$, range 1 – 11), 7.45 for positive affect ($SD = 2.30$, range 2 – 11), 7.36 for negative affect ($SD = 2.41$, range 2 – 11), 7.20 for general health ($SD = 2.45$, range 1 – 11), and 7.33 for physical functioning ($SD = 2.31$, range 1 – 11), respectively.

To select the best fitting longitudinal model of change for examining changes in each of our outcomes before and after child loss, we compared the relative model fit across four longitudinal models: intercept-only, linear change, linear + quadratic change, and a multi-phase model of change. The intercept-only, linear change, linear + quadratic change is based on suggestions from previous research examining resilience to major life stressors (see Galatzer-Levy & Bonanno, 2014; Maccullum et al., 2015; Mancini et al., 2015) and the multi-phase model is based on recent research from Infurna & Luthar (2016; in press). Table 1 compares the model fit across key indicators for the aforementioned models and Figures S1 to S3 in the supplemental materials and Figure 1 graphically illustrate them. When comparing model fit, a lower BIC value is favored, RMSEA values below .05 indicate excellent model fit, and CFI values above .95 indicate excellent model fit (see Hu & Bentler, 1999). We found that consistent across each outcome, the multi-phase longitudinal model out-performed each of the other models, with lower BIC values and RMSEA values below .05 and CFI values above 0.95. Therefore, the longitudinal model of change that we utilize for the central GMM analyses in this study is the multi-phase longitudinal model, which we describe further below.

The multi-phase longitudinal model of change we used consists of three latent factors: child loss average adjustment levels, pre-child loss change, and post-child loss change. Thus, our longitudinal model allowed for variations in individuals' life satisfaction, positive and negative affect, general health, and physical functioning *levels* at the year of the reported child loss (i.e., year 0; *child loss level)*. Because the intercept was set to year 0, the *pre-child loss change* parameter is interpreted as the amount of *change* in life satisfaction, positive and negative affect, general health, and physical functioning from year 0 to year −5. Furthermore, the factor loadings for the pre-child loss change factor for the post-child loss years (i.e., years −1 to −5) were set to 1. This is required for multiphase models in order to facilitate interpretability of the intercept parameter, in addition to ensuring that each change parameter had a proper reference in regards to the intercept for total change observed (see Cudeck & Klebe, 2002; see chapter 6 in Muthén & Muthén, 2012; Ram & Grimm, 2007). Also, allowed to vary was the total amount of change in life satisfaction, positive and negative affect, general health, and physical functioning *following* child loss (year 0 to year 5; *post-child loss change).* Separate latent factors were estimated for pre- and post-child loss change (as opposed to estimating linear and quadratic change), to attain separate estimates for the *total amount of change* that transpired in the years before and after child loss. For example, some individuals may show relative stability prior to child loss followed by substantial and sustained declines thereafter, whereas others may show declines in the years preceding child loss, followed by gradual improvements to near-previous levels. This approach of estimating separate pre- and post-child loss change parameters for individuals provided us the opportunity to model these potential individual differences in how each outcome changed prior to and following child loss. Additionally, as we demonstrated in Table 1, estimating separate parameters for changes before and after child loss led to improved model fit in our longitudinal model of change, a key first step when using GMM (for discussion, see Ram & Grimm, 2009). This permitted for more fully examine the potential non-linearity of change (e.g., declines prior to child loss and improvements following child loss) (see Burke, Shrout, & Bolger, 2007; Infurna & Luthar, 2016; Lucas et al., 2004). Latent basis factors allow for the pattern of change to emerge from the raw data, as opposed to imposing a specific functional form on the shape of change (e.g., linear or quadratic).

Figure 1 illustrates the longitudinal model that we utilize, where the mean and variance parameter was estimated for each latent factor (i.e., child-loss level, pre- and post-child loss change). The factor means describe the extent of change and the variance indicates the extent of between-person differences within the individual trajectories, around the mean trajectory. Along the lines suggested by Infurna and Luthar (2016), we estimated the variance for level and pre- and post-child loss change and allowed (a) the means and variances for each of our latent factors to vary within and across classes and (b) the latent basis estimates to differ across classes (see Infurna & Luthar, in press). That is, the means, variances, and latent basis estimates were not estimated to be the same across trajectories, but allowed to differ across different trajectories. By doing so, this specifically allows for examining the assumption that in fact, there would be less within-group variability in the resilient trajectories, than in others.

Steps for model fitting—We estimated a series of GMMs with 1 through 5 classes to determine the number of distinct classes for each of our outcomes, life satisfaction, positive and negative affect, general health, and physical functioning. To select the best fitting model for each outcome, we used multiple fit statistics, including information criteria (e.g., Bayesian Information Criterion – better fitting models have a lower Bayesian Information Criterion [BIC]; see Nylund, Asparouhov, & Muthén, 2007), entropy (higher values indicate more distinct classes and that individuals are grouped into classes that describe their functional configuration well), approximate likelihood ratio tests (LRTs) that compare the relative fit of models to similarly structured models with one fewer class (Lo, Mendell, & Rubin, 2001), and interpretation of the class parameters through the plotting of group trajectories for their theoretical sensibility and distinctiveness (see Ram & Grimm, 2009). Along the lines suggested (see Muthén, 2004; Nylund et al., 2007; Ram & Grimm, 2009), we used a combination of these fit statistics, with particular emphasis on entropy, the LRTs, and plotting of the trajectories. Overall, we wanted to be conservative in our approach of selecting the model with the most appropriate number of classes to prevent from over-extraction of classes. We provide more information on the model selection criteria for each outcome below and where appropriate, in the supplemental figures, graphically illustrate other potential solutions that could have been selected (see Figure S4).

All models were estimated using *MPlus* 7.1 (see Muthén & Muthén, 1998–2012), with incomplete data accommodated using full information maximum likelihood.

Results

Resilience to Child Loss

Life satisfaction—The top section of Table 2 shows results from a series of models allowing 1 to 5 classes to be estimated in the data examining change in life satisfaction before and after child loss. We determined that the 3-class model provided the most parsimonious fit to the data. This was based on the BIC, entropy, and the two LRTs; although the BIC was lower for the 4-class solution, the LRTs both determined that the 4- and 5-class solutions did not significantly fit better than the 3-class solution.

Figure 2A shows the trajectories of change in life satisfaction for the three classes and Table 3 provides the model parameters. We found evidence of individuals displaying sustained declines in life satisfaction following child loss (chronic low), with 10% of the sample likely to belong to this class. In the chronic low class, life satisfaction dropped, on average, 1.08 points on a 0 to 10 scale from the year prior to child loss (i.e., year −1) to the year of child loss (i.e., year 0), with individuals typically exhibiting sustained lower levels of life satisfaction following child loss. The pre-child loss change estimate is based on the latent basis estimates reported in the bottom of Table 3 (0.34*3.19). The resilient class consisted of 44% of the sample and showed stability in relatively high life satisfaction in the years prior to and following child loss. The moderate class had the largest membership (46%) and on average, parents exhibited slight declines prior to child loss that were sustained following child loss.

As has been argued before (Infurna & Luthar, in press), a key distinguishing feature between the resilient and two identified classes in this sample was that the resilient class showed less variability in pre-child loss change (resilient = 0.05 versus moderate = 1.00) and less variability in levels of life satisfaction at the time of child loss (resilient = 0.83 versus moderate 1.27). This is further exemplified in Figure 3A and 3B, where individuals in the resilient class had life satisfaction scores ranging from 7 to 10 and generally similar rates of change, whereas the moderate class, on average, showed not just lower levels of life satisfaction surrounding child loss but also more within-group variability, with scores ranging from 5 to 10. Within-group variability was still greater in the chronic low group, with scores over time ranging between less than 2 and 9. As a group, therefore, the resilient class showed more stability in life satisfaction and in pre- and post-child loss changes, compared to the moderate and chronic low classes.

Negative affect—The middle section of Table 1 shows results from a series of models allowing 1 to 5 classes to be estimated in the data examining change in negative affect before and after child loss. The 2-class model provided the most parsimonious fit to the data, despite the BIC being lower in the 3-, 4-, and 5-class solutions. Our decision to select the 2-class model was based on the LRTs for the 3-, 4- and 5-class solutions not being statistically significant, indicating that these solutions did not significantly fit better than the 2-class solution.

Figure 2B shows the trajectories of change in negative affect for the two classes and Table 4 provides the model parameters for each class. 56% of individuals were likely to belong to the resilient trajectory characterized by stable, low levels of negative affect. 44% of individuals were likely to belong to a recovery class characterized by increases in negative affect prior to child loss and, on average, a return back to previous levels in the years thereafter.

Findings showed again that there was considerable within-group variability across the sub-groups. Figure 4 graphically illustrates the model-implied trajectories from a subset of participants belonging to each class. As shown, the resilient class (Figure 4A) generally showed more stability in level, pre-child loss and post-child loss change compared to the recovery class (see bottom of Table 4). In comparison, the recovery class (Figure 4B), showed a tremendous amount of variability in the extent to which negative affect changed before and especially after child loss.

Positive affect—Similar to negative affect, a 2-class model provided the most parsimonious fit to the data for positive affect (see middle section of Table 2). We chose the 2-class solution over the 3-class solution, despite the 3- and 5-class solutions having lower BIC values. Furthermore, the LRT for the 3-class solution was marginally significant at $p = .08$ and the entropy value was close to acceptable (0.641). However, we wanted to be conservative in our approach and did not want to over-extract from the data. In the supplemental materials, Figure S4 shows the 3-class solution. In examining the 2-class solution, 21% of participants were likely to belong to the resilient class and 79% belong to a moderate-recovery class. In the 3-class solution, the resilient class was comprised of 10% of the sample and there were two moderate-recovery classes: one recovery class was comprised of 32% of the sample and showed more rapid and full recovery from year −1 to year 1 of child loss, whereas the second recovery class (58%) showed declines prior to child loss and slightly bounced back, but showed sustained declines in the years thereafter.

Figure 2C shows the trajectories of change in positive affect and Table 5 provides the model parameters. In contrast to life satisfaction and negative affect, we found that a fewer proportion of individuals belonged to the resilient class (21%), with their trajectory characterized by stable, high levels of positive affect. The remaining class, moderate-recovery (79%), showed substantial declines in positive affect from the year prior to child loss to the year of child loss, losing, on average, 0.48 points ($d = -0.57$). Our findings suggest that child loss, on average, resulted in sustained declines in positive affect.

Yet again, the resilient and recovery classes showed considerable differences in the amount of within- and between-class variability. This is reported in the bottom of Table 5 and graphically illustrated in Figure 5. The recovery class showed greater variability in changes in positive affect in the years prior to and following child loss.

General health—The bottom section of Table 2 shows results from a series of models allowing 1 to 5 classes to be estimated in the data examining change in general health before and after child loss. We determined that the 2-class model provided the most parsimonious fit to the data. This was based on the BIC, entropy, and the two LRTs; although the BIC was lower for the 3-class solution, the LRTs both determined that the 3-, 4- and 5-class solutions did not significantly fit better than the 2-class solution.

Figure 2D shows the trajectories of change in general health for the two classes and Table 6 provides the model parameters. We found that the largest group displayed low levels of and declines in general health in the years leading up to and following child loss (68%). Conversely, the resilient class was much smaller, with 32% of the sample likely to belong, and on average, showed high, stable levels of general health before and after child loss

A key distinguishing feature between the two classes found for general health is that the declining class showed greater variability in levels (resilient = 117.36 versus chronic poor = 351.21), pre-child loss change (resilient = 20.23 versus chronic poor = 160.56) and post-child loss change (resilient = 52.56 versus chronic poor = 407.06). This is further exemplified in Figure 6A and 5B, where the chronic poor class, on average, showed more within-group variability with scores ranging from 0 to 100, as well as greater variability in changes before and after child loss, compared to general health scores ranging from 60 to 100 in the resilient class and individuals showing similar rates of change.

Physical functioning—We determined that the 3-class model provided the most parsimonious fit to the data for changes in physical functioning before and after child loss (see bottom of Table 2). This was based on the BIC, entropy, and the two LRTs; although the BIC was lower for the 4- and 5-class solutions, the LRTs both determined that the 4- and 5-class solutions did not significantly fit better than the 3-class solution.

Figure 2E shows the trajectories of change in physical functioning for the three classes and Table 7 provides the model parameters. We found that only a small proportion of individuals belonged to the resilient class that was characteristic of stable, healthy levels of physical functioning (16%). We note that for model convergence, the pre- and post-child loss change variances needed to be set to 0 in the resilient class; this was entirely due to the statistical program detailing that the covariance matrix was not positive definite. The remaining two classes showed declines in physical functioning before and after child loss, but differed in their levels of physical functioning at the year of child loss, with the chronic poor class (43%) showing lower levels, compared to the moderate class (41%).

A key distinguishing feature between the three classes is the amount of variability within the classes. Across the three classes for physical functioning, the resilient class showed the least amount of variability in levels (resilient = 2.21, moderate = 656.44, chronic poor = 375.16). This is further exemplified in Figure 8, where the moderate and chronic poor classes, on average, showed greater variability in levels and changes in physical functioning.

Concordance among Outcomes in Class Memberships

In a next step, we investigated the proportion of individuals who were in the resilient class for life satisfaction, positive and negative affect, as well as the two health indicators, general health and physical functioning (see Table 8), by outputting the probable class membership for each person for each indicator. Table 8 shows the concordance of class membership for each of the specific classes. For example, of the 211 people who were classified in the resilient class for life satisfaction, 167 were in the resilient class for negative affect and 72 were in the resilient class for positive affect.

Associations involving vulnerability and protective factors

Next, we compared the subgroup showing resilience across all five indicator*s* to those showing resilience in zero, one, two, three, or four domains, on all the vulnerability and protective factors examined (see Table 9). The goal was to discern which of our examined factors might be potent in differentiating people who clearly did well (or were manifestly resilient) across diverse outcomes, from those who did *not* meet criteria for resilience (or did "less than well" across all five indicators; see Infurna & Luthar, in press; Luthar et al., 1993).

Note that of the 461 individuals who experienced child loss in this sample, only 21 or 5% were resilient across all five outcomes included (Group 5 in Table 9). Conversely, 130 or 28% of the sample did *not* exhibit a resilient trajectory across all five outcomes included (Group 0 in Table 9). Analyses also showed that 99 individuals (21%), 89 individuals (19%), 69 individuals (15%), and 53 individuals (12%) showed a resilient trajectory in one, two, three, or four outcomes (Groups 1, 2, 3, and 4), respectively.

Table 9 presents the socio-demographic and psychosocial characteristics for the six subgroups. One-way analyses of variance indicated significant group differences on all three psychosocial factors with effect sizes in the middle to large range, as follows: Reliable comfort ($\eta^2 = .12$), social connectedness ($\eta^2 = .35$), and everyday role functioning ($\eta^2 = .20$). Comparisons on demographic indices were significant for age, gender, education, and marital status.

Follow-up Tukey comparisons of group means showed that participants in the zero resilience group (Group 0) clearly fared significantly worse than all other groups, showing less reliable comfort, less social connectedness, and poorer everyday role functioning. Individuals showing resilience in all domains, Group 5, significantly differed from all groups in showing better social connectedness, but on reliable comfort, their means were statistically comparable to Groups 3 and 4, with both faring better than both Groups 0, 1, and 2. Overall, findings suggested the strongest risk-modifying potential for social connectedness and sustained everyday role functioning, followed by anticipation of reliable support.

Our approach, thus far, solely examined which of our vulnerability and protective factors were *associated* with resilient outcomes, but not the relative *predictive* strength of each. In order to more stringently test the unique associations for each vulnerability and protective factor, we entered them into a regression to predict the number of outcomes individuals were resilient in (scores ranging from 0 to 5). Table 10 shows our results. Model 1 in Table 10 included socio-demographics and we found that attaining more years of education and being married were each predictive of being resilient across more outcomes. In Model 2, we included our psychosocial characteristics and found that anticipating more reliable comfort (β = 0.14), greater social connectedness (β = .45), and everyday role functioning (β = 0.10) were each uniquely predictive of being resilient across more outcomes. The effects of education and marital status were rendered non-significant with the inclusion of the vulnerability and protective factors.

Discussion

In this prospective panel-survey covering 11-years, the proportion of individuals showing resilience to child loss differed across indicators: 44%, 56%, 21%, 32%, and 16% for life satisfaction, negative affect, positive affect, general health, and physical functioning, respectively. When considered collectively, only 5% of participants showed resilience across the five domains, whereas 28% did *not* show a resilient trajectory across all outcomes. Significant vulnerability and protective factors – those distinguishing clearly non-resilient versus clearly resilient groups from others – were connections with social networks, everyday role functioning and anticipation of support when distressed.

Resilience to Child Loss

Our findings contribute substantively to the literature on bereaved parents (and more broadly, resilience to major life stressors) in demonstrating that resilience, as indicated by steady healthy psychological and physical functioning, is actually far from normative with the death of a child. Whereas rates as high as 64% have been documented in past research (Maccullum et al., 2015), we found that only 5% of parents who had lost their child continued to function steadily well, considering just five adjustment domains. If we had considered additional outcomes, such as substance use, or sleep quality, this rate would have likely been lower. Overall, our findings are consistent with evidence that child bereaved parents, on average, report poorer psychological well-being even many years after child loss (Floyd et al., 2013; Lehman et al., 1987; Rogers et al., 2008; Wijngaards-de Meij et al., 2005).

In future research on bereaved parents, our findings highlight the need to consider multiple conceptually important indicators in operationalizing resilience. Had we solely included just one indicator as did Maccullum and colleagues (2015), then a different story would have emerged from these data. As suggested at the outset of this paper, parents may view their life as generally satisfactory despite experiencing child loss because of turning their focus to work or engagement in hobbies, but this does not translate to equanimity of emotions on a daily basis or health functioning. Positive affect dimensions of calmness, peacefulness, and being a happy person, may well be diminished following the loss of a child, being more immediately affected (Fried et al., 2015). This is further demonstrated in our inclusion of pertinent health outcomes, which have been less of a focus in resilience research (for discussion, see Ukraintseva et al., in press; Whitson et al., 2016). We showed that declines were not solely confined to the well-being domain, but most individuals additionally showed declines in perceptions of general health and physical functioning as a result of child loss.

Findings of this study also help inform the larger resilience literature in important ways. Most importantly, perhaps, these findings underscore the dangers of conferring labels of resilience based on one or two measured outcomes, as resilience in a particular domain can clearly co-exist with deficits in other conceptually important spheres. Taking this one step further, we believe that making statements regarding rates of resilience from research that used a single indicator is a significant concern (Infurna & Luthar, in press), because this can potentially lead to public dialogue of blaming individuals if they struggle for considerable amounts of time.

Second, we hope that this study will help begin to change implicit presumptions that resilience is a unidimensional construct. The resilience literature in adulthood and old age has suggested that resilience is “across-the-board” when in most instances only one outcome was assessed. As we have demonstrated in this study, resilience is a multidimensional construct, with a great deal of cross-domain variability across outcomes; individuals’ ability to be resilient in one outcome will likely coincide with declines or recovery in other pertinent outcomes. For example, we found that 44% of individuals showed a resilient trajectory for life satisfaction, but only 16% of individuals showed a resilient trajectory for both life satisfaction and positive affect. This is akin to research that has been done on post-traumatic growth, where multiple pertinent outcomes are simultaneously examined to ascertain the degree to which individuals may potentially show enduring improvements in specific areas following adversity (see Jayawickreme & Blackie, 2014). Multidimensional strategies must be considered to avoid overestimations in the proportion of people that are declared resilient to significant adversities (Infurna & Luthar, in press; Luthar, et al., 2000).

From a methodological standpoint, our findings confirm that there is in fact tremendous variability both within- and between-sub-groups; this is a critical issue to be considered in assumptions applied in future resilience research based on GMM. As shown in the Tables and Figures, people in the resilient classes showed more stability before and after child loss, whereas those in the moderate, recovery or chronic low/poor classes showed more variability, overall. Besides empirically demonstrating these group differences, our analyses also show that individuals can take different *paths* towards resilience or recovery. The approach of allowing for the classes to differ in how much they vary between one another is especially critical due to a recent simulation study by Diallo and colleagues (2016) who documented that relaxing the assumptions of homogeneity of variance does in fact improve model fit and leads to better ability to recover distinct sub-groups and protects against over-extraction of distinct sub-groups. More specifically, Diallo and colleagues (2016) found that assuming homogeneity of variance led to over-extraction of classes; data were simulated for one-class underlying the sample, and by applying the aforementioned assumption of homogeneity of variance lead to 4 classes being found in the data. Using empirical data, Infurna and Grimm (in press) further demonstrated the importance of the homogeneity of variance of assumption by showing that relaxing this assumption led to improved model fit and better identification of sub-groups in the data. In sum, results of this study confirm the critical need for researchers to allow for such variability; the failure to allow for these in assumptions applied at the outset can lead to misleading findings about the nature and sizes of resilient trajectories (Infurna & Grimm, in press; Infurna & Luthar, 2016; in press).

Our methodological approach and empirical findings raise the additional important issue of what is the most appropriate approach/method for examining the nature of resilience to major life stressors. For example, what is the importance of categorizing participants into the commonly found classes (e.g., resilient, recovery, growth, and chronic low) based on their trajectories over time (for discussion, see Infurna & Grimm, in press)? As shown in Figure 2, the distinctiveness between classes is mostly due to differences in levels in the outcome rather than on the trajectory. One potential explanation for these findings is that individuals may have a set-point prior to the adversity and tend to deviate around their set-point with few people showing dramatic and sustained changes (Diener et al., 2006). Another explanation is that the yearly assessments are too sparse and mask changes that could be transpiring between assessments, with more closely spaced assessments required. We acknowledge that these arguments are largely speculative, but nonetheless, we feel that the issues warrant explicit discussion in the literature. Most importantly, our findings raise the larger issue of whether there is, or can be, any “gold-standard” for operationalizing resilience; as definition of success in the face of adversity must always be conceptually linked to the nature of the adversity that is under consideration in a given study (Luthar et al., 2000).

Future research is warranted that compares and contrasts the various approaches to studying resilience to adversity, such as GMM and latent growth curve (multilevel) modeling. In GMM, the goal is to examine whether distinct classes or sub-groups underlie the data. However, it could be potentially difficult to isolate those individuals who experienced dramatic and sustained declines because of the adversity encountered or very high levels of distress that begin not until 1–2 years following the adversity. In contrast, the advantage of latent growth curve (multilevel) modeling is the potential to examine the nature of change over time and to identify factors that are associated with between-person variation in such changes (e.g., Grimm et al., 2017; Lucas, 2007). By utilizing this approach in the context of studying resilience, the focus would be less on examining the nature of change, and more on distilling salient vulnerability and protective factors that are associated with relatively positive trajectories in the outcome of interest. Thus, this analytic strategy could be one way to better match the goal of moving away from “rates” of resilience and toward predicting meaningful variation in psychological functioning and physical health following adversity and better informing interventions for who to target. Conceptually, this would be along the lines suggested by Rutter (2006, 2012) who maintained that resilience is best defined in terms of individuals’ manifestation of relatively better outcomes than others who experienced the same adversity. Rutter (2006, 2012) additionally asserted that there is no requirement that resilience should be defined as individuals exhibiting superior functioning in relation to the population as a whole (who did not experience the adversity).

Vulnerability and Protective Factors

Our findings focused on distilling salient vulnerability and protective factors associated with resilience have implications for future interventions. Results of these analyses showed that more than several demographics indicators, three potentially modifiable indicators were each significantly linked with being resilient in more outcomes. Parents who showed poor functioning across all five domains reported considerably lower levels of social connectedness, everyday role functioning, and anticipated comfort when distressed. Unfortunately, by its very nature, grief can lead people to withdraw from others (Fried et al., 2015). From an intervention perspective, our findings support suggestions that if bereaved parents can have continued connection with supportive others, and maintain everyday routines to the degree possible, this will be critical in helping work through child loss, mitigating the intensity or duration of parents' mourning (Stoebe et al., 2002).

We additionally observed in Table 9 and Model 1 in Table 10 that men, those with more years of educational attainment, and those who were married were each more likely to be resilient across more outcomes. These findings are in line with previous research showing that women show poorer adjustment to child loss (Wijngaards-de Meij et al., 2005, 2008), which could be due to women typically being children's primary caregivers (Luthar & Ciciolla, 2015). Obtaining more years of educational attainment is likely associated with resilient adaptation because more educated people tend to know and use more adaptive and compensatory strategies (Adler et al., 1994). For example, educational attainment is associated with psychosocial resources of perceived control that individuals can utilize in stressful contexts to buffer against declines in subjective well-being (Aneshensel, Botticello, & Yamatoto-Mitani, 2004; Lachman & Weaver, 1998; Luthar & Ciciolla, 2015). Our sample consisted of a large age-heterogeneous sample and we did not find that being younger or older to be associated with a higher likelihood of showing resilience. This is contrary to our expectations and empirical evidence showing that child loss would be more detrimental to individuals in young adulthood and midlife (Keesee et al., 2008; Neugarten & Hagestad, 1976).

Limitations and Conclusions

Longitudinal panel-surveys have advantages of large samples allowing the study of changes with adversity, but are limited in the breadth of variables measured, including constructs such as coping strategies known to be protective with child bereavement (Wijngaards-de Meij et al., 2005, 2008). Additionally, we did not have information on cause of death of the child in this study. There is likely to be greater heterogeneity in child loss and this may influence parents' post-loss adjustment. For example, parents' adjustment may vary if the loss was expected due to prolonged illness versus sudden (Floyd et al., 2013), and also differ depending on the age of the child, and whether the reported death included pregnancy losses and stillbirths. Third, we were unable to examine the specific mechanisms underlying the resilience-promoting effects of social connectedness and as noted earlier, these may sometimes have represented "signs" of resilience as much as its "causes". Fourth, we did not have access to measures of mental health symptoms or clinical measures of distress, such as depressive symptoms or grief, which have been studied previously (Maccullum et al., 2015). The outcomes included are primarily designed to assess "normal" levels of functioning and less on clinical distress. Especially in the face of serious life adversities, resilience researchers may be more fundamentally interested in examining more severe levels of dysfunction. Therefore, we acknowledge that the targeted outcomes may only capture peripheral aspects of mental and physical health and future research is needed that applies our approach to examining concordance of the domains examined with measures of mental health symptoms following child loss.

Lastly, it is important to acknowledge that because most of the distinctiveness observed between classes for each outcome were primarily due to differences in levels of functioning and less so based on the trajectory, this has implications for the interpretation of the analyses that focus on predicting resilience. In this instance, it is potentially the case that the prediction analyses could be interpreted as correlations between known predictors of levels of health and well-being. As discussed above, future research is warranted to examine further the methodological approaches to studying resilience, with the identification of vulnerability and protective factors being of paramount importance.

These limitations notwithstanding, our findings contribute significantly to the resilience literature, clearly attesting to the erroneousness of any generalized declarations that resilience is common (Infurna & Luthar, 2016). As human adaptation is multidimensional in nature (Baltes, 1987), the proportion of individuals who exhibit resilient trajectories will inevitably differ drastically depending on the type and number of indicators examined (Infurna & Luthar, in press). For parents who experience the tragedy of the death of their child, our resolve, as resilience researchers, must be to eschew any declarations on rates of resilience and remain focused, instead, on discerning how best we might aid their recovery through powerful grief or despair.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- A multidimensional approach to examining resilience to major life stressors is proposed
- Findings showed that resilience to child loss is multidimensional, differing based on outcome
- Social resources were the strongest predictors of resilience to child loss
- Resilience is shown to be not as commonplace as discussed in the literature

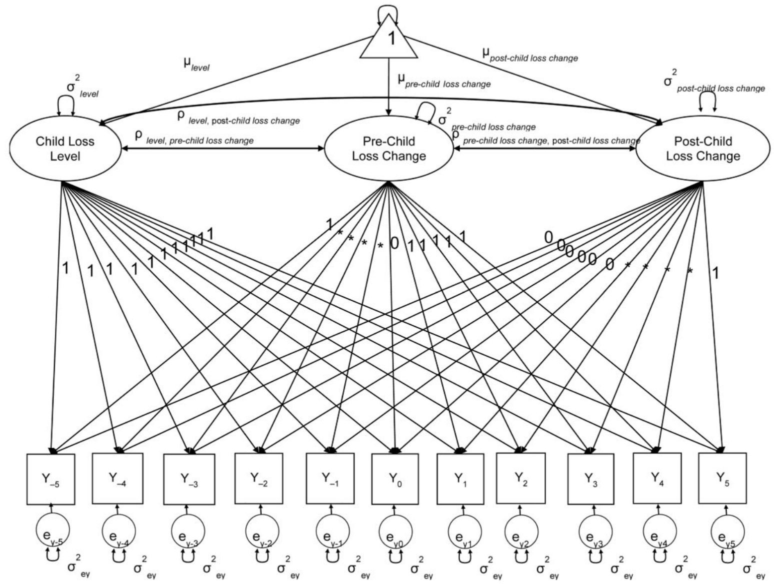

Figure 1.

Graphical representation of the structural equation model for our multi-phase model of change. We estimated three latent factors: child loss level, pre-child loss change, and post-child loss change. Child loss level refers to how individuals may report varying levels of life satisfaction, positive and negative affect, general health, and physical functioning at the year of the reported child loss. Pre-child loss change refers to the total amount of change in life satisfaction, positive and negative affect, general health, and physical functioning in the years prior to child loss. Post-child loss change refers to the total amount of change following child loss and whether individuals are able to return back to their previous levels of functioning. The factor loadings for level are all set to 1 and the factor loadings that are not labeled for pre-child loss change and post-child loss change are freely estimated. The factor loadings for the pre-child loss change factor for the post-child loss years (i.e., years −1 to −5) were set to 1 to facilitate interpretability of the intercept parameter and for reference of the intercept for the amount of change observed (see Cudeck & Klebe, 2002; see chapter 6 in Muthén & Muthén, 2012; Ram & Grimm, 2007). We estimated the variances in child loss level, pre-child loss change, and post-child loss change, along with their covariances. In the analyses where GMM was implemented the variances, covariances, residual variances, and factor loadings were estimated to differ across the classes that were estimated. We used observations of life satisfaction, positive and negative affect, general health, and physical functioning that were taken five years prior to and five years following the year of child loss (Y).

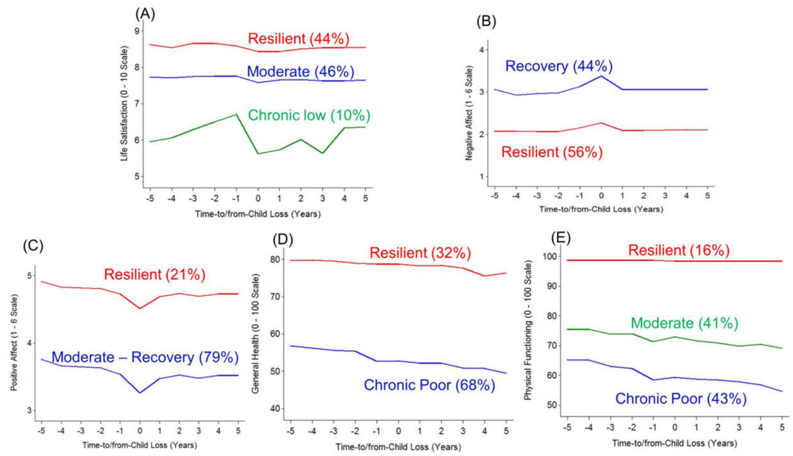

Figure 2.

Illustration of trajectories of change for (A) life satisfaction, (B) negative affect, (C) positive affect, (D) general health, and (E) physical functioning before and after child loss. GMM results showed that for life satisfaction, three trajectories best represented our sample, 44% were Resilient, showing stable, high levels of life satisfaction; 46% showed slight declines prior to child loss (Moderate), and 10% showed sustained low levels and declines in life satisfaction (Chronic Low). For negative affect, Part B, a 2-class solution provided the best fit, with 56% belonging to the Resilient trajectory with low, stable negative affect, and 44% in a Recovery trajectory, with increases in negative affect prior to child loss, on average, and returns back to previous levels thereafter. For positive affect, Part C, a 2-class solution best fit the data, with 21% of participants in the stable Resilience and 79% in the Moderate-Recovery trajectory. For general health, Part D, a 2-class solution best fit the data, with 32% of participants in the stable resilience class and 68% belonging to the chronic poor trajectory. For physical functioning, Part E, a 3-class solution best fit the population under study, with 16% belonging to the resilient trajectory, 43% showing moderate levels, and 41% in a class characteristic of chronic poor levels.

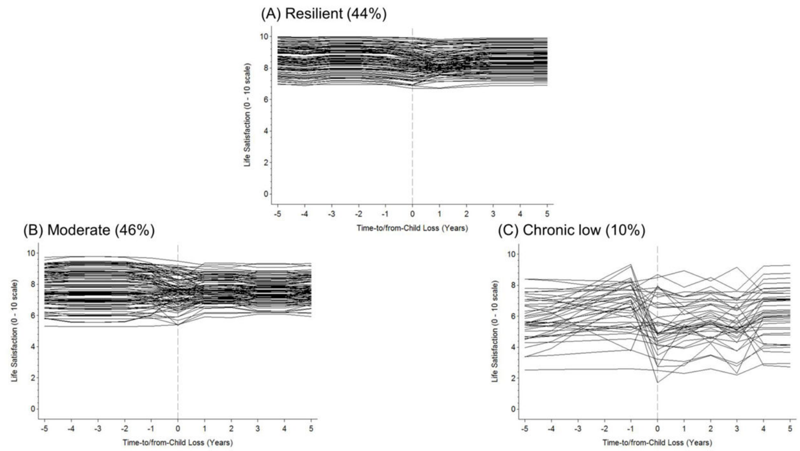

Figure 3.

We modeled the model-implied trajectories for a subset of 100 participants in the resilient (A) and moderate (B) classes and for all participants in the chronic low (C) class for life satisfaction. There was a great deal of heterogeneity in the degree to which life satisfaction changed both within- and between-sub-groups. Individuals in the moderate and chronic low classes showed more variability in their levels and rates of change in life satisfaction before and after child loss, as compared to the resilient class. Note that classification is not 100% accurate. For life satisfaction, the average probability of accurate classification was 86.1%, 85.2%, and 91.7% for resilient, moderate, and chronic classes, respectively (see Table 3).

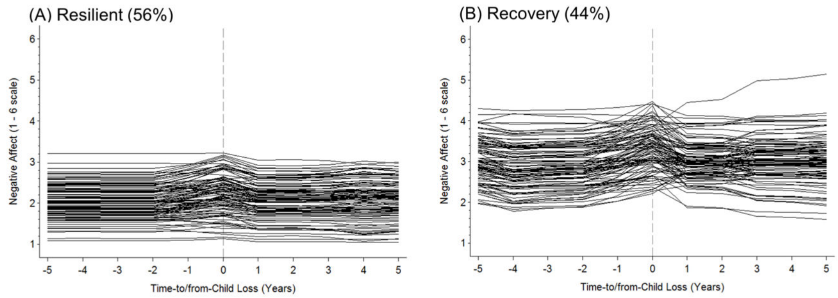

Figure 4.
We modeled the model-implied trajectories for a subset of 100 participants in the resilient (A) and recovery (B) classes for negative affect. There were differences in the amount of variability within- and between- sub-groups, with the recovery classes showing the greatest amount of variability. Note that classification is not 100% accurate. For negative affect, the average probability of accurate classification was 91.9% and 91.7% for resilient and recovery classes, respectively (see Table 4).

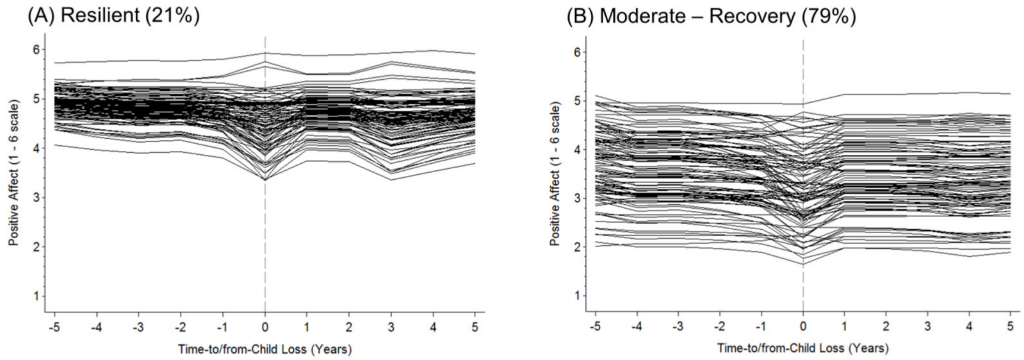

Figure 5.
We modeled the model-implied trajectories for a subset of 100 participants in the resilient class (A) and moderate-recovery class (B) for positive affect. There was a great deal of heterogeneity in the degree to which positive affect changed both within- and between- sub-groups. Individuals in the moderate-recovery class showed more variability in their levels and rates of change in positive affect, as compared to the resilient class. Note that classification is not 100% accurate. For positive affect, the average probability of accurate classification was 86.0% and 97.2% for resilient and moderate-recovery classes, respectively (see Table 5).

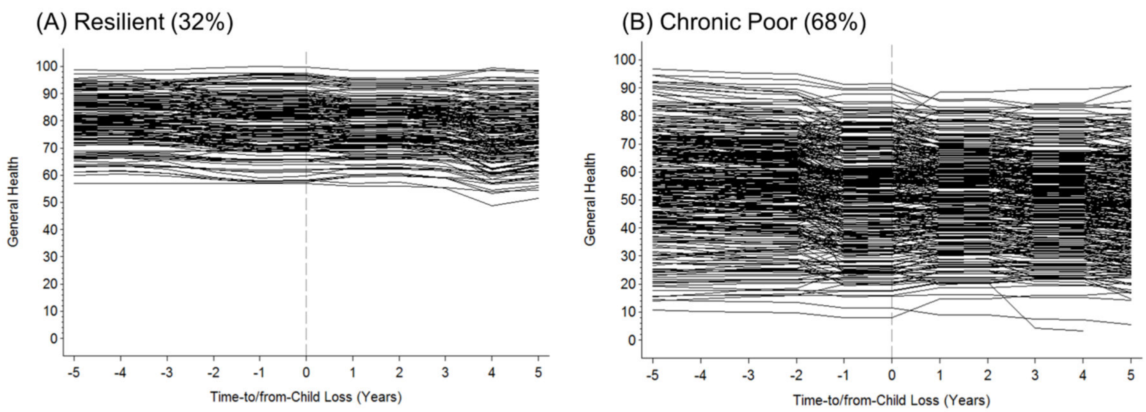

Figure 6.

We modeled the model-implied trajectories for a subset of 100 participants in the resilient class (A) and chronic poor class (B) for general health. There was a great deal of heterogeneity in the degree to which general health changed both within- and between- sub-groups. Individuals in the chronic poor class showed more variability in their levels and rates of change in general health, as compared to the resilient class. Note that classification is not 100% accurate. For general health, the average probability of accurate classification was 89.0% and 95.7% for resilient and chronic poor classes, respectively (see Table 6).

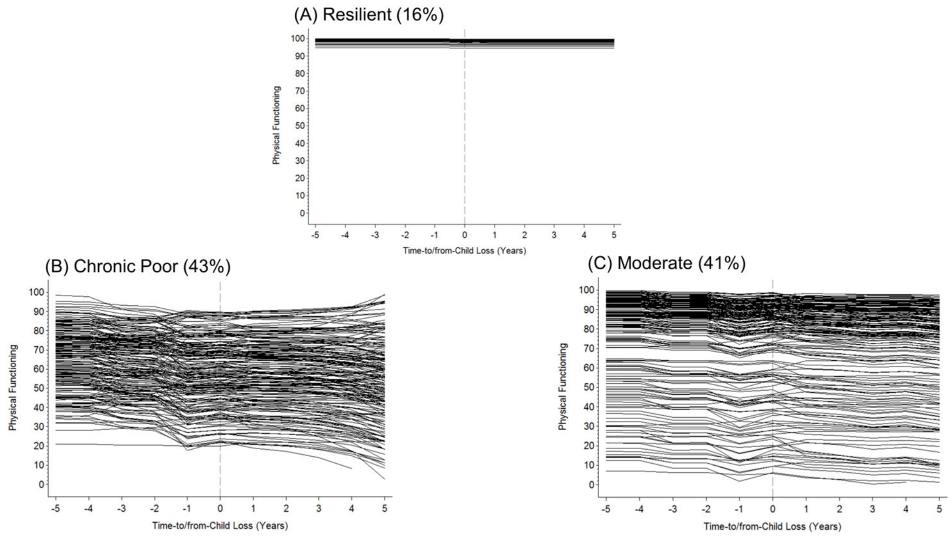

Figure 7.
We modeled the model-implied trajectories for all of the participants in the resilient class (A) and a subset of 100 participants in the chronic poor (B), and moderate (C) classes for physical functioning. Note that classification is not 100% accurate. For physical functioning, the average probability of accurate classification was 97.9%, 90.7%, and 93.5% for resilient, moderate, and chronic poor classes, respectively (see Table 7).

Table 1

Comparing Model Fit Across Longitudinal Models of Change to Ascertain the Best Fitting Longitudinal Model to Utilize in Growth Mixture Modeling.

	Intercept only	Linear	Linear + Quadratic	Multi-Phase
Life Satisfaction				
Fit statistics				
BIC	12,484	12,477	12,478	12,410
RMSEA	0.075	0.073	0.073	0.039
CFI	0.879	0.887	0.889	0.974
Negative Affect				
Fit statistics				
BIC	7,779	7,781	7,766	7,685
RMSEA	0.079	0.079	0.075	0.038
CFI	0.888	0.890	0.900	0.979
Positive Affect				
Fit statistics				
BIC	8,327	8,303	8,285	8,228
RMSEA	0.079	0.074	0.069	0.036
CFI	0.889	0.904	0.916	0.981
General Health				
Fit statistics				
BIC	27,345	27,288	27,291	27,198
RMSEA	0.088	0.078	0.078	0.039
CFI	0.914	0.935	0.935	0.987
Physical Functioning				
Fit statistics				
BIC	29,062	29,018	29,020	28,984
RMSEA	0.087	0.078	0.078	0.061
CFI	0.922	0.937	0.938	0.970

Note. $N = 461$. In accordance with previous research (see Galatzer-Levy & Bonanno, 2014; Maccullum et al., 2015; Mancini et al., 2015), in the linear and linear + quadratic longitudinal models, the slope variances were set to 0. We note that in the multi-phase model, the slope variances were freely estimated and not set to 0.

Table 2

Model Fit Statistics for Growth Mixture Models Determining Number of Classes for How Life Satisfaction, Negative Affect, Positive Affect, General Health, and Physical Functioning Change Before and After Child Loss.

	1-Class	2-Class	3-Class	4-Class	5-Class
Life Satisfaction					
Sample size					
$N_{c=1}$	461	294.99	211.09	198.33	33.33
$N_{c=2}$		166.01	47.09	26.82	41.91
$N_{c=3}$			202.82	3.08	11.99
$N_{c=4}$				232.78	172.66
$N_{c=5}$					201.11
Fit statistics					
BIC	12,410	11,756	11,722	11,683	11,711
Entropy		0.758	0.699	0.808	0.740
Vuong-Lo-Mendell-Rubin LRT		0.0000	0.0054	0.3569	0.7300
Lo-Mendell-Rubin Adjusted LRT		0.0000	0.0057	0.3604	0.7306
Negative Affect					
Sample size					
$N_{c=1}$	461	258.87	214.05	118.05	20.61
$N_{c=2}$		202.13	115.14	43.95	41.18
$N_{c=3}$			131.81	101.29	92.64
$N_{c=4}$				197.71	238.19
$N_{c=5}$					68.38
Fit statistics					
BIC	7,685	7,131	7,112	7,099	7,060
Entropy		0.727	0.697	0.719	0.776
Vuong-Lo-Mendell-Rubin LRT		0.0000	0.9421	0.1043	0.5513
Lo-Mendell-Rubin Adjusted LRT		0.0000	0.9427	0.1069	0.5525
Positive Affect					
Sample size					

	1-Class	2-Class	3-Class	4-Class	5-Class
$N_{c=1}$	461	96.06	267.62	164.83	6.79
$N_{c=2}$		364.94	47.89	64.11	97.39
$N_{c=3}$			145.89	140.16	38.84
$N_{c=4}$				91.91	182.17
$N_{c=5}$					135.82
Fit statistics					
BIC	8,228	8,074	8,062	8,064	7,984
Entropy		0.827	0.641	0.595	0.631
Vuong-Lo-Mendell-Rubin LRT		0.0021	0.0777	0.7601	0.3315
Lo-Mendell-Rubin Adjusted LRT		0.0022	0.0795	0.7608	0.3374
General Health					
Sample size					
$N_{c=1}$	461	311.75	160.24	155.54	226.60
$N_{c=2}$		149.25	229.30	143.86	91.57
$N_{c=3}$			71.46	73.40	1.46
$N_{c=4}$				88.20	84.20
$N_{c=5}$					56.17
Fit statistics					
BIC	27,198	26,949	26,943	26,964	26,958
Entropy		0.768	0.739	0.694	0.728
Vuong-Lo-Mendell-Rubin LRT		0.0030	0.1957	0.7882	0.1298
Lo-Mendell-Rubin Adjusted LRT		0.0032	0.1195	0.7916	0.1326
Physical Functioning					
Sample size					
$N_{c=1}$	461	139.41	72.60	95.93	62.78
$N_{c=2}$		321.59	189.19	83.63	182.34
$N_{c=3}$			199.23	61.41	51.25
$N_{c=4}$				220.02	58.65
$N_{c=5}$					105.99
Fit statistics					

	1-Class	2-Class	3-Class	4-Class	5-Class
BIC	28,984	27,332	27,010	26,719	26,719
Entropy		0.961	0.851	0.832	0.813
Vuong-Lo-Mendell-Rubin LRT		0.0017	0.0151	0.6133	0.0745
Lo-Mendell-Rubin Adjusted LRT		0.0018	0.0159	0.6165	0.0757

Note. $N = 461$.

Table 3

Fixed and Random Effects for Change in Life Satisfaction Before and After Child Loss.

	Resilient	Moderate	Chronic low
Life Satisfaction			
Sample size	202.82	211.09	47.09
Average probability of class membership	0.861	0.852	0.917
Factor means			
Level	8.43* (0.12)	7.58* (0.15)	5.62* (0.67)
Pre-child loss slope	0.19 (0.12)	0.15 (0.15)	0.34 (0.37)
Post-child loss slope	−0.07 (0.08)	−0.08 (0.11)	0.40 (0.43)
Variances			
Level	0.83* (0.18)	1.27* (0.28)	4.56* (1.73)
Pre-child loss slope	0.05 (0.13)	1.00* (0.48)	0.77 (0.85)
Post-child loss slope	0.05 (0.09)	0.92 (0.49)	1.90 (1.66)
Covariance between level and pre-child loss slope	−0.08 (0.13)	−0.50* (0.25)	−1.40 (1.20)
Covariance between level and post-child loss slope	−0.03 (0.06)	−0.13 (0.20)	0.00
Covariance between pre- and post-child loss slope	−0.03 (0.04)	−0.60 (0.40)	0.00
Residual	0.36* (0.04)	1.23* (0.13)	4.31* (0.53)

Note. Resilient: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.59, 1.20, 1.21, 0.83, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 2.64, 1.67, 1.07, 1.08, 1 for the time interval −5 years to 5 years in relation to child loss.

Recovery: Parameter estimates for pre-event slope latent basis slope factor: 1, 1.16, 1.17, 1.14, 0.86, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.95, 0.90, 1.25, 1.26, 1 for the time interval −5 years to 5 years in relation to child loss.

Chronic low: Parameter estimates for pre-event slope latent basis slope factor: 1, 1.32, 1.98, 2.59, 3.19, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, −0.56, 0.13, −0.80, 0.94, 1 for the time interval −5 years to 5 years in relation to child loss.

*$p < .05$.

Table 4

Fixed and Random Effects for Change in Negative Affect Before and After Child Loss.

	Resilient	Recovery
Negative Affect		
Sample size	258.87	202.13
Average probability of class membership	0.919	0.917
Factor means		
Level	2.27* (0.08)	3.38* (0.10)
Pre-child loss slope	−0.20* (0.05)	−0.32* (0.13)
Post-child loss slope	0.03 (0.05)	0.00 (0.19)
Variances		
Level	0.32* (0.05)	0.56* (0.11)
Pre-child loss slope	0.10* (0.04)	0.21 (0.16)
Post-child loss slope	0.09* (0.04)	0.71* (0.25)
Covariance between level and pre-child loss slope	−0.10* (0.04)	−0.17 (0.09)
Covariance between level and post-child loss slope	0.06* (0.03)	−0.20 (0.15)
Covariance between pre- and post-child loss slope	−0.07* (0.03)	−0.07 (0.16)
Residual	0.14* (0.01)	0.62* (0.06)

Note. Resilient: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.99, 1.02, 1.02, 0.59, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.77, 0.71, 0.86, 1.23, 1 for the time interval −5 years to 5 years in relation to child loss.

Recovery: Parameter estimates for pre-event slope latent basis slope factor: 1, 1.42, 1.30, 1.24, 0.79, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.54, 0.59, 0.89, 0.92, 1 for the time interval −5 years to 5 years in relation to child loss.

* $p < .05$.

Table 5

Fixed and Random Effects for Change in Positive Affect Before and After Child Loss.

	Resilient	Moderate – Recovery
Positive Affect		
Sample size	96.06	364.94
Average probability of pattern membership	0.860	0.972
Factor means		
Level	4.47* (0.10)	3.28* (0.07)
Pre-child loss slope	0.42* (0.11)	0.48* (0.08)
Post-child loss slope	−0.16* (0.07)	−0.27* (0.08)
Variances		
Level	0.37* (0.09)	0.70* (0.08)
Pre-child loss slope	0.34* (0.10)	0.58* (0.17)
Post-child loss slope	0.06 (0.06)	0.49* (0.17)
Covariance between level and pre-child loss slope	−0.30* (0.08)	−0.33* (0.10)
Covariance between level and post-child loss slope	0.12* (0.04)	0.17* (0.08)
Covariance between pre- and post-child loss slope	−0.13 (0.07)	−0.42* (0.08)
Residual	0.11* (0.02)	0.49* (0.03)

Note. Resilient: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.86, 0.76, 0.80, 0.62, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.85, 0.90, 1.88, 1.41, 1 for the time interval −5 years to 5 years in relation to child loss.

Moderate – Recovery: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.78, 0.80, 0.70, 0.55, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.89, 0.90, 0.96, 1.10, 1 for the time interval −5 years to 5 years in relation to child loss.

* $p < .05$.

Table 6

Fixed and Random Effects for Change in General Health Before and After Child Loss.

	Resilient	Chronic poor
General Health		
Sample size	149.25	311.75
Average probability of pattern membership	0.890	0.957
Factor means		
Level	78.77* (1.35)	52.77* (1.42)
Pre-child loss slope	0.90 (1.38)	3.99* (1.37)
Post-child loss slope	−3.33 (1.88)	−7.36* (1.81)
Variances		
Level	117.36* (21.23)	351.21* (31.43)
Pre-child loss slope	20.23 (14.03)	160.56* (57.77)
Post-child loss slope	52.56* (23.29)	407.06* (108.79)
Covariance between level and pre-child loss slope	−17.63 (11.80)	−50.64 (36.59)
Covariance between level and post-child loss slope	10.48 (15.07)	−1.63 (52.82)
Covariance between pre- and post-child loss slope	−22.17 (16.39)	−208.63* (72.05)
Residual	37.73* (3.85)	152.36* (7.42)

Note. Resilient: Parameter estimates for pre-event slope latent basis slope factor: 1, 1.12, 0.87, 0.24, −0.11, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.44, 0.39, 0.60, 1.26, 1 for the time interval −5 years to 5 years in relation to child loss.

Chronic poor: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.87, 0.2, 0.66, −0.03, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.63, 0.62, 0.80, 0.81, 1 for the time interval −5 years to 5 years in relation to child loss.

* $p < .05$.

Table 7

Fixed and Random Effects for Change in Physical Functioning Before and After Child Loss.

	Resilient	Moderate	Chronic poor
Physical functioning			
Sample size	72.14	189.26	199.60
Average probability of class membership	0.979	0.907	0.935
Factor means			
Level	98.35* (0.32)	72.97* (2.58)	59.28* (2.70)
Pre-child loss slope	0.36 (0.25)	2.53 (1.35)	6.00 (3.61)
Post-child loss slope	−0.23 (0.21)	−6.39* (1.47)	−10.71* (3.67)
Variances			
Level	2.21* (0.55)	656.44* (84.48)	375.16* (61.19)
Pre-child loss slope	0.00	14.14 (9.38)	210.79 (108.30)
Post-child loss slope	0.00	59.45 (45.01)	757.59 (439.90)
Covariance between level and pre-child loss slope	0.00	−10.20 (18.64)	−95.70 (88.09)
Covariance between level and post-child loss slope	0.00	16.98 (31.88)	153.82 (107.86)
Covariance between pre- and post-child loss slope	0.00	−8.35 (20.97)	−390.92* (139.63)
Residual	3.52* (0.67)	50.10* (7.05)	371.95* (42.02)

Note. Resilient: Parameter estimates for pre-event slope latent basis slope factor: 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 1, 1, 1, 1, 1 for the time interval −5 years to 5 years in relation to child loss.

Moderate: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.99, 0.34, 0.37, −0.69, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.61, 0.72, 0.88, 0.80, 1 for the time interval −5 years to 5 years in relation to child loss.

Chronic poor: Parameter estimates for pre-event slope latent basis slope factor: 1, 0.96, 0.62, 0.49, −0.15, 0, 1, 1, 1, 1, 1 and parameter estimates for post-event slope latent basis slope factor 0, 0, 0, 0, 0, 0.61, 0.64, 0.70, 0.80, 1 for the time interval −5 years to 5 years in relation to child loss.

* $p < .05$.

Table 8

Concordance Across Classes for Life Satisfaction, Negative Affect, Positive Affect, General Health, and Physical Functioning

			Negative Affect		Positive Affect		General Health		Physical Functioning		
Outcome	**Class**	**N**	**Resilient**	**Recovery**	**Resilient**	**Moderate – Recovery**	**Resilient**	**Chronic poor**	**Resilient**	**Moderate**	**Chronic poor**
Life Satisfaction	Resilient	211	167	44	72	139	94	117	50	92	69
	Recovery	210	93	117	26	184	56	154	22	90	98
	Chronic low	40	4	36	2	38	3	37	1	11	28
	Resilient	264			95	169	125	139	60	118	86
Negative Affect	Recovery	197			5	192	29	168	13	76	109
Positive Affect	Resilient	100					70	30	36	44	20
	Moderate – Recovery	361					84	277	37	149	175
General Health	Resilient	154							55	71	27
	Chronic poor	307							19	122	167
Physical Functioning	Resilient	73									
	Moderate	193									
	Chronic poor	195									

Note. $N = 461$. Number of individuals in each class is from the outcome probabilities and may not exactly match onto the percentages reported in Table 2.

Table 9

Comparison of Participants Based on Number of Adjustment Domains (Life Satisfaction, Negative Affect, Positive Affect, General Health, and Physical Functioning) in which they were Classified as Resilient

	Group 0: Not resilient in all domains N= 130		Group 1: Resilient in any 1 domain N= 99		Group 2: Resilient in any 2 domains N= 89		Group 3: Resilient in any 3 domains N= 69		Group 4: Resilient in any 4 domains N= 53		Group 5: Resilient in all 5 domains N= 21			
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**F/χ^2**	**η^2**
Vulnerability and Protective Factors														
Reliable comfort	4.34_{d}	1.62	$4.93_{c,d}$	1.60	$5.07_{c,d}$	1.41	$5.50_{a,b,c}$	1.29	$5.76_{a,b}$	1.09	6.08_{a}	0.97	11.14^{*}	0.12
Social connectedness	40.67_{e}	27.81	62.75_{d}	27.14	$68.29_{c,d}$	24.57	$81.16_{b,c}$	19.49	$86.32_{a,b}$	17.72	98.81_{a}	3.76	49.13^{*}	0.35
Role functioning	38.52_{d}	42.43	$57.35_{c,d}$	41.52	$70.59_{b,c}$	37.59	$81.25_{a,b}$	30.79	$86.67_{a,b}$	27.77	93.65_{a}	17.06	21.50^{*}	0.20
Demographics														
Age	53.88_{b}	19.40	59.32_{b}	21.03	54.76_{b}	20.47	54.09_{b}	20.10	52.25_{b}	19.92	39.10_{a}	12.47	3.85^{*}	0.04
	%		%		%		%		%		%			
Women	$67\%_{b}$		$64\%_{b}$		$56\%_{b}$		$58\%_{b}$		$57\%_{b}$		$29\%_{a}$		2.57^{*}	0.03
Education	$30\%_{b}$		$39\%_{b}$		$44\%_{b}$		$43\%_{b}$		$49\%_{b}$		$76\%_{a}$		3.97^{*}	0.04
Married	$45\%_{a,b}$		$39\%_{b}$		$64\%_{a,b}$		$52\%_{a,b}$		$66\%_{a,b}$		$67\%_{a}$		4.07	0.04

Note. N=461. Group 0: N = 130 or 28% of the whole bereaved sample; Group 1: N = 99 or 21%; Group 2: N = 89 or 19%; Group 3: N = 69 or 15%; Group 4: N = 53 or 12%; Group 5: N = 21 or 5%. Means with the same subscript are not significantly different from each other. η^2 of .03, .10, and .30 are considered small, medium, and large effect sizes, respectively, see Cohen, 1988.

$^{*}p < .05$.

Table 10

Regression Models to Determine Unique Prediction of Socio-Demographic Factors and Risk-Modifiers in The Number of Resilience Outcomes.

	Model 1		Model 2	
	Estimate (SE)	**β**	**Estimate (SE)**	**β**
Intercept	1.68* (0.10)		1.78* (0.08)	
Demographics				
Age	−0.004 (0.004)	−0.05	−0.001 (0.003)	−0.01
Age squared	0.0001 (0.0002)	0.04	−0.0001 (0.002)	−0.03
Women	−0.27 (0.14)	−0.09	−0.17 (0.12)	−0.06
Education	0.48* (0.15)	0.15	0.19 (0.12)	0.06
Married	0.37* (0.14)	0.12	0.18 (0.12)	0.06
Vulnerability and Protective Factors				
Reliable comfort			0.14* (0.04)	0.14
Social connectedness			0.02* (0.002)	0.45
Role functioning			0.004* (0.002)	0.10
R Squared	0.0646		0.3734	

Note. N = 461. The socio-demographics and risk-modifiers assessments were taken from the year of the reported child loss.

* $p < .05$.