Health Psychology

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# Do Multiple Health Events Reduce Resilience When Compared With Single Events?

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***Objective:*** The impact of multiple major life stressors is hypothesized to reduce the probability of resilience and increase rates of mortality. However, this hypothesis lacks strong empirical support because of the lack of prospective evidence. This study investigated whether experiencing multiple major health events diminishes rates of resilience and increases rates of mortality using a large population-based prospective cohort. ***Method:*** There were $n = 1{,}395$ individuals sampled from the Health and Retirement Study (HRS) and examined prospectively from 2 years before 4 years after either single or multiple health events (lung disease, heart disease, stroke, or cancer). Distinct depression and resilience trajectories were identified using latent growth mixture modeling (LGMM). These trajectories were compared on rates of mortality 4 years after the health events. ***Results:*** Findings indicated that 4 trajectories best fit the data including resilience, emergent postevent depression, chronic pre-to-post depression, and depressed prior followed by improvement. Analyses demonstrate that multiple health events do not decrease rates of resilience but do increase the severity of symptoms among those on the emergent depression trajectory. Emergent depression increased mortality compared with all others but among those in this class, rates were not different in response to single versus multiple health events. ***Conclusions:*** Multiple major stressors do not reduce rates of resilience. The emergence of depression after health events does significantly increase risk for mortality regardless of the number of events.

*Keywords:* resilience, depression, health, latent growth mixture modeling, mortality

There is abundant evidence that depression is highly comorbid with significant physical illness (Moussavi et al., 2007) including myocardial infarction (MI; van Melle et al., 2004), stroke (Whyte & Mulsant, 2002), cancer (Spiegel & Giese-Davis, 2003), and lung disease (Maurer et al., 2008) among others (Katon, 2003). There are seemingly paradoxical findings in the literature with evidence both that depression predates the onset of illness (Brown, Varghese, & McEwen, 2004) and evidence indicating that depression is a consequence of illness (de Jonge, van den Brink, Spijkerman, & Ormel, 2006). Recent work utilized large population based cohort studies to capture the longitudinal course of depression in response to health events prospectively, demonstrating that both findings are accurate. In these studies, heterogeneous depression populations are present including both a population for whom clinical levels of depression symptomatology is present before the event and a population that develops depression secondary to the health event (e.g., Bombardier, Hoekstra, Dikmen, & Fann, 2016; Burton, Galatzer-Levy, & Bonanno, 2015). Parsing these populations is important as they diverge in their risk for mortality secondary to their physical illness (Rudisch & Nemeroff, 2003), with those whose depression onset is secondary to the event having greatly increased mortality rates (Galatzer-Levy & Bonanno, 2014).

More important, the majority of individuals neither develops depression as a consequence of illness nor are depressed before the illness. These individuals can be described as psychologically resilient (Bonanno, 2004). Some researchers have sought to measure resilience as a trait (e.g., a resilient type) that can be captured by a single administration of a questionnaire (e.g., Connor & Davidson, 2003). Although methodologically expedient, this approach suffers from serious conceptual and empirical limitations. For example, resilience scales overestimate the predictive utility of trait measures, which rarely explain more than a small portion of long-term variance, and have yet to be shown to distinguish among multiple patterns of long-term outcome (Bonanno, 2004, 2012; Bonanno & Mancini, 2008; Bonanno, Romero, & Klein, 2015). A more conceptually and empirically robust approach is to identify

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psychological resilience as a stable trajectory of healthy functioning (e.g., Bonanno, 2004; Bonanno, Westphal, & Mancini, 2011). Although this approach is more methodologically demanding, requiring multiple longitudinal assessment, a growing number of studies have identified the resilience trajectory as the most common outcome pattern in response to a range of potentially traumatic events, including traumatic injury (deRoon-Cassini, Mancini, Rusch, & Bonanno, 2010), bereavement (Bonanno et al., 2002; Galatzer-Levy & Bonanno, 2014), violence (Galatzer-Levy et al., 2012), spinal cord lesion (Bonanno, Kennedy, Galatzer-Levy, Lude, & Elfström, 2012), and combat deployment (Bonanno et al., 2012). More important, a stable resilience trajectory has also been the most commonly observed pattern when measured before and after life-threatening illnesses (Bonanno, Galea, Bucciarelli, & Vlahov, 2007; Burton et al., 2015; Galatzer-Levy & Bonanno, 2014).

A crucial but as yet unanswered question pertains to the prevalence of resilience after multiple health events. As individuals age they inevitably experience multiple health events, which may impact the proportion of resilience. Theories related to cumulative burden of allostatic load (Juster, McEwen, & Lupien, 2010) indicate that the interaction between physiological and psychological stressors leads to impaired functioning and increased mortality risk (Seeman, McEwen, Rowe, & Singer, 2001). This may indicate that as individuals encounter an increasing number of health events, they will be at greater risk for the emergence of depression, and subsequent increased risk for mortality above and beyond the burden of the physical illness (Gunn et al., 2012).

To decrease mortality risk as well as other negative sequelae of health events, particularly among older adults, it is vital to parse who is at greatest risk for these outcomes. Thus, identifying unique trajectories of functioning related to one or multiple health events will help to determine for whom targeted interventions are most necessary.

In the current investigation we attempt to parse the complex relationship between increased health burden and risk for the onset of depression as they relate to increased risk for mortality. Following hypotheses about cumulative burden, we hypothesized that increased numbers of major health events will be associated with decreased rates of resilience, increased rates of depression onset, and increased rates of mortality.

## Method

We conducted analyses utilizing data from the Health and Retirement Study (HRS), a nationally representative study exploring numerous aspects of aging among American adults. The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) at the University of Michigan, with data collected every 2 years. At the time of first data collection, informed consent was obtained from all participants after the nature of the study and its procedure had been explained. The investigation was carried out in accordance with the latest declaration of Helsinki. The first wave of data was collected in 1994, and have since been made available to the public and to researchers for analysis. Ten waves of data were utilized in the current analysis (drawn from the RAND HRS vM database; RAND HRS Data, 2014), with approval of the study design by the Institutional Review Board of Teachers College, Columbia University.

### Participants

Using the RAND HRS vM database, participants were selected who had, at one time, reported that they had never been diagnosed with cancer, stroke, lung disease, or heart disease—and who were diagnosed with one (or more) of those illnesses in a subsequent interview. From this subsample, we selected individuals who had reported their level of depression during at least three time points, including the time point immediately before and after diagnosis. At least the two previously mentioned time points as well as one subsequent time point (either one or two time points after diagnosis) were required for inclusion in the final sample. Data were organized using a floating baseline methodology (e.g., Galatzer-Levy, Bonanno, & Mancini, 2010), with each individual's 6-year trajectory centered at their time point of their first-reported health event, and including one pre-event time point.

The final sample consisted of 1,395 participants (54.6% women, 45.4% men), with an average age of 74.31 ($SD$ = 10.21, range 46–101) at the time point when the health event(s) were experienced or diagnosed. Of this sample, 73% had experienced one health event, and 27% had experienced multiple health events (see Table 1 for additional demographic characteristics). Of the sample, 17% had depression data available at three time points, and 71% had depression data for all four time points.

### Measures

**Health events.** For the purpose of this study, severe health events with a discrete temporal onset were chosen. These were cancer, stroke, heart disease, or lung disease. At each wave of data collection, participants were asked whether they had a diagnosis of one of these illnesses that they had not had in the previous wave of data collection. Data collected for health event status was based on an individual answering "yes" to the question of whether they had developed the illness since their most recent interview, and did not report a previous history of that illness. For each participant, all health events were coded as "1" for presence of the new diagnosis or "0" for absence in the wave of first event onset. Subsequently, all outcome measures for the participant were centered on the time point of diagnosis.

**Depression symptomatology.** Symptoms of depression were measured using eight items from the Center for Epidemiologic Studies–Depression (CES-D) scale (Radloff, 1977), which has demonstrated adequate validity in samples of older adults (Kohout, Berkman, Evans, & Cornoni-Huntley, 1993). The scale asked participants whether they experienced symptoms such as "I could not get going" or "I felt depressed" over the course of the past week (with 1 = *yes*, and 0 = *no*), with a cutoff of four indicating a clinically relevant elevation of symptoms.

**Death records.** The HRS utilized information from the National Death Index to indicate whether a participant had died at a given time point. For the purpose of the current study, a dummy-coded variable was constructed to indicate mortality beyond the last measured time point. That is, whether a participant had died by the next data collection time, 4–6 years after the health event(s) were diagnosed. Information about cause of death was not available for this sample.

Table 1
*Participant Demographic Characteristics*

| Variable | One health event $n = 1{,}019$ | Multiple health events $n = 376$ | Total sample $n = 1{,}395$ |
|---|---|---|---|
| Male | 45.4% | 45.2% | 45.4% |
| Female | 54.6% | 54.8% | 54.6% |
| Age | 74.42 (10.44) [46–101] | 74.02 (9.55) [48–99] | 74.31 (10.21) [46–101] |
| Education | | | |
| No high school | 37.7% | 32.2% | 36.2% |
| High school graduate | 62.3% | 67.8% | 63.8% |
| Income | | | |
| <\$10k | 47% | 52.7% | 48.5% |
| \$10k–100k | 31% | 24.7% | 28.9% |
| >\$100k | 22% | 22.6% | 22.6% |
| Event type | | [a] | |
| Cancer | 8.2% | 15.4% | 6.0% |
| Lung | 14.0% | 15.7% | 11.8% |
| Heart | 63.3% | 25.5% | 60.6% |
| Stroke | 14.4% | 15.2% | 21.6% |

[a] Findings were 100% because each person had multiple health events; *SD*s in parentheses, range in brackets.

## Results

### Unconditional Model

We utilized a latent growth mixture modeling (LGMM) approach using Mplus version 7.0 (Muthen & Muthen, 1998–2010), to identify the optimal number of depression trajectories for the sample as a whole. A series of models with an increasing number of possible classes were compared (categorizing participants into one, two, three, four, and five classes), with the slope and intercept freely estimated among the classes. For purposes of model convergence, the quadratic term was fixed for all analyses.

To identify the best-fitting number of classes, we assessed several fit criteria—the Akaike, Bayesian, and sample-size adjusted Bayesian information criterions, entropy values, Lo-Mendell-Rubin, and bootstrap likelihood ratio tests (see Table 2). The lower the information criteria of the Akaike and Bayesian, the better the model fits. An entropy value indicates how well the theoretical probability distribution approximates the distribution in the data, with a higher value indicating less noise and greater certainty in model classification (Ram & Grimm, 2009). The Lo-Mendell-Rubin and bootstrap likelihood tests provide significance tests, indicating whether adding an additional class to the model allows it to better fit the data. The decision as to the best-fitting model took into account values on the above-mentioned tests, as well as theoretical interpretability and parsimony (Lubke & Muthén, 2005). As the models increased from one to five, they showed improved fit on all information criteria. However, the 5-class model showed a reduction in entropy and a nonsignificant Lo-Mendell-Rubin test. These considerations, in conjunction with the model showing best theoretical coherence and parsimony, indicate that a 4-class solution best fit the data (see Figure 1).

The largest class was the Resilient class (64.2% of the sample), reporting low depression across all time points. This class was characterized by a low initial intercept ($b = 0.68$, $SE = 0.07$, $p < .001$), a significant overall slope ($b = 0.35$, $SE = 0.09$, $p < .001$), and a nonsignificant quadratic parameter ($b = -0.03$, $SE = 0.03$, $p = .26$). The next largest class was the Depressed—Improved class (14.2% of the sample), who reported depression symptoms at the clinical cut-off on average before the onset of the health event, and showed a decrease in symptoms afterward. This class was characterized by a moderate initial intercept ($b = 3.73$, $SE = 0.36$, $p < .001$), a significant negative overall slope ($b = -1.73$, $SE =$

Table 2
*Fit Indices for One–Five Class Unconditional Growth Mixture Model of Health Event(s)*

| | Model | | | | |
|---|---|---|---|---|---|
| Fit index | One class | Two classes | Three classes | *Four classes* | Five classes |
| AIC | 19,999.07 | 19,556.66 | 19,377.19 | *19,210.36* | 19,116.29 |
| BIC | 20,051.48 | 19,630.03 | 19,471.52 | *19,325.65* | 19,252.56 |
| SSBIC | 20,019.71 | 19,585.56 | 19,414.34 | *19,255.77* | 19,169.96 |
| Entropy | — | .90 | .85 | *.84* | .83 |
| LMR | — | $p < .01$ | $p < .01$ | $p = .06$ | $p = .28$ |
| BLRT | — | $p < .01$ | $p < .01$ | $p < .01$ | $p < .01$ |

*Note.* *Italics* indicate selected model; AIC = Akaike information criterion; BIC = Bayesian information criterion; SSBIC = sample-size-adjusted Bayesian information criterion; LMR = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood-ratio test.

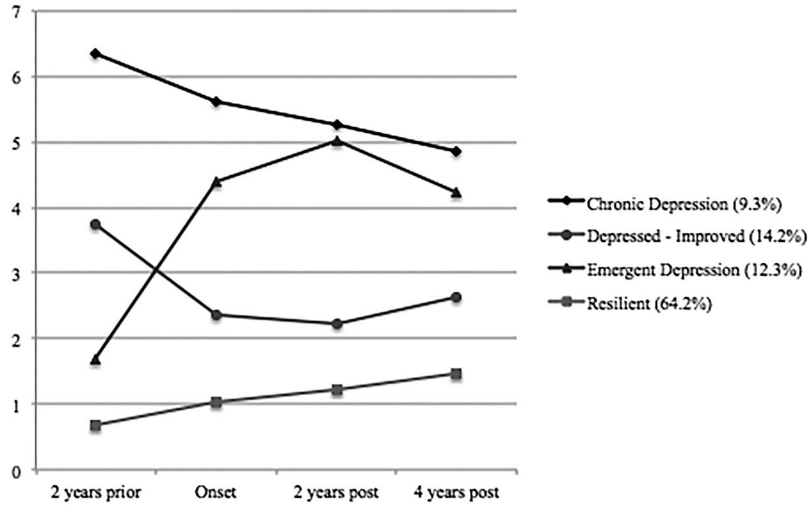


*Figure 1.* Four class unconditional model of CES-D depression trajectories ($n$ = 1,395).

0.63, $p < .01$), and a significant quadratic parameter ($b$ = 0.46, $SE$ = 0.18, $p < .01$). The third-largest class was the Emergent Depression class (12.3% of the sample), reporting few symptoms before onset of the health event(s), and worsening depression over time, with onset of worsening depression symptoms after the health event. This class was characterized by a low initial intercept ($b$ = 1.71, $SE$ = 0.21, $p < .001$), a significant positive slope ($b$ = 3.48, $SE$ = 0.52, $p < .001$), and a significant negative quadratic parameter ($b$ = −0.88, $SE$ = 0.18, $p < .001$). The fourth and smallest class was the Chronic Depression class (9.3% of the sample), who reported higher depression across all time points. This class was characterized by a high initial intercept ($b$ = 6.35, $SE$ = 0.15, $p < .001$), a nonsignificant overall slope ($b$ = −0.74, $SE$ = 0.43, $p$ = .08), and nonsignificant quadratic parameter ($b$ = 0.08, $SE$ = 0.13, $p$ = .55).

## Conditional Model With Known Class (Number of Health Events)

To examine the effects of number of health events experienced in the same time period (one vs. multiple) on depression trajectories, we analyzed the chosen four-class solution from the unconditional model using number of health events as a known class variable. The results of this analysis indicated the same four classes among participants with one health event and those with multiple events, with entropy of .902 indicating the model continued to fit the data when the known class variable was included (see Figure 2). In the one-event group, 61.7% were classified in the Resilient group, 19.3% in the Emergent Depression group, 10% in the Chronic Depression group, and 9% in the Depressed-Improved group. In the multiple-events group, 60% were classified in the

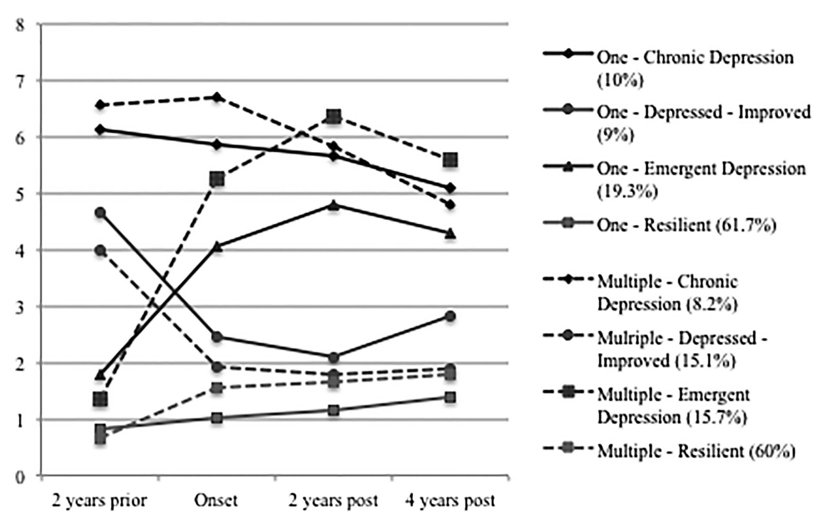


*Figure 2.* Conditional model known class analysis (number of health events) with 4 classes.

Resilient group, 15.7% in the Emergent Depression group, 15.1% in the Depressed-Improved group, and 8.2% in the Chronic Depression group. Multinomial regression analyses were conducted, testing difference in likelihood of class membership based on the known class variable, using the Resilient class as the reference class. Results indicated no effect for any group, with no difference in membership likelihood for the Chronic Depression class ($b = -0.01$, $SE = 0.33$), the Depressed-Improved class ($b = -0.07$, $SE = 0.35$), or the Emergent Depression class ($b = -0.06$, $SE = 0.44$), when compared with the Resilient class. That is, having experienced multiple health events did not significantly increase likelihood of membership in any class other than the Resilient class.

Next, a Wald test was conducted to investigate whether trajectory parameters differed by known class (see Table 3). The overall test was significant, indicating that the trajectories did differ for those with one health event versus multiple. When specific trajectories were compared, it was found that in the Emergent Depression class, those who experienced multiple health events had a trajectory with a significantly steeper slope and quadratic parameter. These findings indicate that for those who experience multiple health events and first experience elevated depression after the onset of their events, they become more depressed more quickly than their counterparts who experienced one health event.

## Conditional Model With Covariates

To investigate demographic predictors of class membership, we ran a conditional model using age, gender, financial assets, and education level as covariates (see Table 4). To aid in model convergence, age and financial assets were standardized before they were entered into the regression model. For the first set of analyses, the Resilient class served as the comparison class. Compared with the Resilient class, participants in the Chronic Depression class were more likely to be younger, female, and have not completed high school. Those in the Depressed–Improved and Emergent Depression classes were significantly more likely to be female, and have a high school education or greater as well, when compared with the Resilient class. In a second analysis using the Chronic Depression class as a reference class, participants in the Depressed–Improved and Emergent Depression classes were significantly more likely to be older and have graduated from high school. Those in the Resilient class were significantly more likely to be older, male, and have graduated from high school than those participants in the Chronic Depression class. When interactions terms for the covariates by known class (one vs. multiple health events), no significant results emerged—in other words, these covariate predictors of class membership did not differ by number of health events. Additionally, type of health event (lung disease, heart disease, cancer, and stroke) did not predict membership in any of the four classes.

## Mortality Associated With Class Membership

By three time points after the onset of one or more health events, 17.4% of the sample had died. To determine whether mortality risk differed by class membership, we conducted an analysis of distal outcome, controlling for age, gender, and number of health events, comparing trajectories for likelihood of mortality (see Table 5). Results show that those in the Emergent Depression class were significantly more likely to be dead three time points after onset than those in the Chronic Depression, Depressed–Improved and Resilient classes, regardless of number of health events experienced.

# Discussion

In this study, we identified prospective trajectories of depression after the experience of one or multiple health events in a population-based sample of older adults. The investigation sought to answer questions about the relationship between health events and depression over time, to identify differences in outcomes between individuals who experience one versus multiple health events (specifically, whether resilience decreased with the experience of more than one adverse event), and whether membership in a particular trajectory increased risk for mortality. These findings have important implications for preventive care and the development of targeted interventions.

Table 3
*Wald Test for Trajectory Parameters by Known Class Variable*

| Classes | One event | Multiple events | *df* | Wald Test | *p* |
|---|---|---|---|---|---|
| Class 1–Chronic depression | | | | | |
| Intercept | 6.133 | 6.597 | 1 | .956 | .328 |
| Slope | −.126 | .281 | | .176 | .675 |
| Quadratic | −.075 | −.297 | | .509 | .475 |
| Class 2–Depressed - improved | | | | | |
| Intercept | 1.789 | 1.373 | 1 | .400 | .527 |
| Slope | 2.918 | 4.895 | | .152 | .696 |
| Quadratic | −.695 | −1.168 | | .211 | .646 |
| Class 3–Emergent depression | | | | | |
| Intercept | 4.654 | 3.950 | 1 | .624 | .430 |
| Slope | −2.837 | −2.358 | | 10.071 | $.001^{**}$ |
| Quadratic | .754 | .583 | | 6.124 | $.013^{*}$ |
| Class 4–Resilient | | | | | |
| Intercept | .813 | .686 | 1 | .932 | .334 |
| Slope | .193 | .940 | | 3.538 | .060 |
| Quadratic | −.002 | −.195 | | 1.591 | .207 |
| Overall test | | | 12 | 28.46 | $.004^{**}$ |

$^{*} p < .05$. $^{**} p < .01$.

Table 4
*Multinomial Regression Estimates for Covariate Predictors of Class Membership*

| Classes | Covariate | Est. | *SE* |
|---|---|---|---|
| Compared to resilient | | | |
| Chronic depression | Known class | −.01 | .33 |
| | Age | −.43 | .11** |
| | Gender | .99 | .21** |
| | Financial assets | −3.97 | 2.41 |
| | Education | .70 | .27** |
| Depressed - Improved | Known class | −.07 | .35 |
| | Age | .05 | .11 |
| | Gender | .75 | .21** |
| | Financial assets | −.56 | .48 |
| | Education | .77 | .27** |
| Emergent depression | Known class | −.25 | .34 |
| | Age | −.09 | .09 |
| | Gender | .74 | .19** |
| | Financial assets | −.23 | .19 |
| | Education | 1.24 | .14** |
| Compared to chronic depression | | | |
| Depressed - Improved | Known class | −.06 | .44 |
| | Age | .49 | .14** |
| | Gender | −.25 | .28 |
| | Financial assets | 3.41 | 2.44 |
| | Education | .70 | .27** |
| Emergent depression | Known class | −.24 | .46 |
| | Age | .34 | .14* |
| | Gender | −.26 | .28 |
| | Financial assets | 3.74 | 2.44 |
| | Education | .77 | .27** |
| Resilient | Known class | .01 | .33 |
| | Age | .44 | .11** |
| | Gender | −.99 | .21** |
| | Financial assets | 3.98 | 2.41 |
| | Education | 1.26 | .21** |

* $p < .05$. ** $p < .01$.

In line with previous studies of depression trajectories after adverse health events (e.g., Bonanno et al., 2012; Burton et al., 2015; Galatzer-Levy & Bonanno, 2014), four distinct prospective trajectories of depression were identified in this study. The first and by far the modal outcome was resilience—that is, low depression from before the onset of the event persisting across all time points. The second was characterized by elevated depression symptoms before the onset of the health event, with gradual lessening of symptoms over time. The third group showed minimal depression before the onset of the health event, but subsequently experienced elevated symptomatology for several years afterward, and the final group was characterized by elevated depression from before the event, and persisting over time. Thus, the findings in this study provide additional evidence for distinct depression trajectories after adverse life events.

Because resilience has been found to be the most commonly experienced outcome after traumatic experiences and health events (e.g., Bonanno, 2004; Bonanno et al., 2011), it was of interest to investigate whether the experience of multiple health events reduced resilience. Results from the known class analysis showed no difference in the likelihood of membership in the Resilient class—that is, the proportion of resilience among individuals with multiple health events was not reduced compared with those with one health event, adding further evidence that though reactions to adverse events are heterogeneous, most individuals do not experience significant long-term distress as a result. This finding has implications for a more nuanced understanding of cumulative disease burden—that is, it appears that some individuals are at greater risk for adverse outcomes in the presence of multiple comorbidities than others.

Following, compared with all other classes, resilient individuals were more likely to be older, male, and less likely to have graduated high school. As women are more likely to experience depression (Piccinelli & Wilkinson, 2000), the gender finding was unsurprising. Older age as a predictor of resilience may be related to findings that older adults significantly expect lower health-related quality of life secondary to age (Sarkisian, Hays, & Mangione, 2002). The finding of lower education attainment associating with resilience was somewhat surprising, though other studies investigating resilience after traumatic events (e.g., Bonanno et al., 2007) have shown similar associations. It is possible, in this particular sample of older adults, that there may have been a cohort effect, whereby older individuals (who were more likely to be resilient), may also have fewer years of education. This speculation will benefit from further exploration. Experience of any particular health event (stroke, cancer, heart disease, or lung disease) did not predict membership in any of the classes, though more specific information about illness severity was not available in this study. Finally, having experienced multiple health events did not significantly predict class membership, nor reduce the proportion of resilience.

When comparing those participants with one health event to those with multiple health events, a significant difference was found among participants in the Emergent Depression class. For

Table 5
*Chi-Square Test for Distal Outcome of Mortality at 6 Years Postonset*

| Classes | Odds ratio[a] | *OR* 95% CI | $\chi^2$ | *p*-value |
|---|---|---|---|---|
| Chronic depression vs. depressed - improved | — | — | .20 | .655 |
| Chronic depression vs. emergent depression | — | — | 9.19 | .002 |
| Chronic depression vs. resilient | .60 | [.32–1.12] | 3.44 | .063 |
| Depressed - Improved vs. emergent depression | — | — | 6.31 | .012 |
| Depressed - Improved vs. resilient | .73 | [.42–1.27] | 1.45 | .228 |
| Emergent depression vs. resilient | 1.72 | [1.08–2.73] | 4.38 | .036 |
| Overall test | — | — | 11.00 | .012 |

*Note*. CI = confidence interval.
[a] With resilient as the referent class.

those who experienced multiple health events, individuals in this class became more depressed after the event, with sustained elevation of symptoms, than their counterparts with one health event. It appears that this group is particularly at risk for negative outcomes, as the Emergent Depression class (for both one and multiple health events) had a significantly greater mortality risk 6 years after onset than any other group (relative to those in the both the Resilient and Chronic Depression classes). This finding replicates a result of greater mortality risk among individuals who had a heart attack, and experienced a subsequent rise in depression symptoms (Galatzer-Levy & Bonanno, 2014). Though there are many possible explanations for this finding, including inflammatory processes that impact all comorbidities (Slavich & Irwin, 2014), and heightened allostatic load (Seeman et al., 2001), it appears this group is at greatest risk. Because health comorbidities are the rule rather than the exception in late life (Jaur & Stoddard, 1999), assessing depression continually in a primary care setting, as well as early intervention, will help to reduce the likelihood of adverse outcomes, and associated health care costs (Pan Knapp, Yeh, Chen, & McCrone, 2013). Additionally, it will help direct resources and treatment toward those individuals most likely to experience negative outcomes, as opposed to those who will not develop depression symptomatology (specifically, those in the Resilient class).

## Limitations

Because this study was conducted among a sample of older adults, it will require future research to determine whether heterogeneous outcome patterns after multiple health events earlier in the life span lead to similar outcomes. It is possible that as individuals age, and both expect and experience more physical problems, the negative response to multiple health events lessens (Sarkisian et al., 2002). The limited number of psychological variables collected and the spacing of interviews (2 years) hinder the ability to generalize these findings. Additionally, the lack of specific information about these health events and subsequent mortality limits the ability to investigate the effects of illness severity on class membership and mortality outcomes. This is particularly difficult in regard to the lack of specific information about health events available in this dataset. It is possible that variability in type, severity and staging of cancer, types of heart and lung diseases, and location and stroke severity might impact trajectory membership, and should be a focus of future study in this area. Furthermore, possible retrospective bias in memory for health events cannot be ruled out in this sample, for reasons such as older age in the HRS, and time since the previous interview (Herzog & Rodgers, 1989).

The use of a quasi-experimental design, with repeated measures of depression collected before and after major health events, is inherently limited in making causal inferences. Indeed, it cannot be assumed that the health events "caused" a depression response, just as it cannot be assumed that lack of a depression response (resilience) was not because of other factors (such as better treatment or less severe illness). Future life span research with more frequent data collection, adequate comparison groups, and more detailed health information (e.g., type and adequacy of treatment) would greatly add to this line of inquiry.

Despite these limitations, the findings in this study add to the body of literature examining unique trajectories of functioning after adverse events, with resilience as the most likely outcome. Additionally, in directly comparing individuals who experienced one health event in a single time period with those who experienced multiple events, we found that resilience is not reduced—an important indication that resilience is a robust phenomenon even after the added burden of multiple adverse health events. There was an important difference between those who experienced one health event and those with multiple events, however, which for those in the Emergent Depression class, those with multiple health events experienced a steeper elevation in symptoms than did those with one health event. For the overall sample, those in the Emergent Depression class were at greater risk for mortality 6 years after the onset of their first health event, indicating that these individuals may most greatly benefit from intervention. These findings have important implications for preventive care among older adults.

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