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Beyond normality in the study of bereavement: Heterogeneity in depression outcomes following loss in older adults

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ABSTRACT

Studies of individual differences in bereavement have revealed prototypical patterns of outcome. However, many of these studies were conducted prior to the advent of sophisticated contemporary data analytic techniques. For example, Bonanno et al. (2002) used rudimentary categorization procedures to identify unique trajectories of depression symptomatology from approximately 3 years prior to 4 years following conjugal loss in a representative sample of older American adults. In the current study, we revisited these same data using Latent Class Growth Analysis (LCGA) to derive trajectories and test predictors. LCGA is a technique well-suited for modeling empirically- and conceptually-derived heterogeneous longitudinal patterns while simultaneously modeling predictors of those longitudinal patterns. We uncovered four discrete trajectories similar in shape and proportion to the previous analyses: *Resilience* (characterized by little or no depression; 66.3%), *Chronic Grief* (characterized by depression following loss, alleviated by 4 years post-loss; 9.1%), *_Pre-existing Chronic Depression* (ongoing high pre- through post-loss depression; 14.5%), and *Depressed-Improved* (characterized by high pre-loss depression that decreases following loss; 10.1%). Using this analytic strategy, we were able to examine multiple hypotheses about bereavement simultaneously. Health, financial stress, and emotional stability emerged as strong predictors of variability in depression only for some trajectories, indicating that depression levels do not have a common etiology across all the bereaved. As such, we find that identifying distinct patterns informs both the course and etiology of depression in response to bereavement.

Introduction

Depression in response to bereavement has often presented with confusing and seemingly paradoxical results. In a meta-analysis, bereavement was shown to be one of the most prominent and consistent risk factors for depression among the elderly (Cole & Dendukuri, 2003), and longitudinal analyses of the course of psychopathology in bereavement have shown that depression sharply increases following a loss (Norris & Murrell, 1990). However, bereavement studied prospectively from before to after the loss has also shown that the bereaved are characterized by emotional stability rather than extreme reactions (Heyman & Gianturco, 1973).

What might account for these apparently conflicting findings? One possible explanation may be the high non-normal level of variability observed in depression scores following loss (Onrust, Cuijpers, Smit, & Bohlmeijer, 2007). This variability may not be unique to bereavement, but might instead be a characteristic of measured depression in non-clinical populations (Radloff, 1977). Variability following such a distribution level may not be successfully captured in statistical models that sample from the mean, as is the case in the above studies and commonly the case in the study of bereavement (Mancini, Bonanno, & Clark, 2011), because such models assume homogeneity characterized by a single normal distribution (Judd, McClelland, & Ryan, 2009).

A preliminary map of trajectories of bereavement response

Attempts to explore the variability intrinsic to depression following loss have revealed surprising results. In an attempt to ascertain if this variability fits into patterns over time, Bonanno et al. (2002) "mapped" distinct and clinically meaningful trajectories of response to loss over time in a sample of American older adults. These included a pattern of stable low depression (Resilience); a pattern characterized by moderate to severe depression

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after the loss that lasted several months or longer before gradually returning to baseline level of functioning (Common Grief or Recovery); a sharp incline in symptoms of depression following loss that did not lessen by 18 months (Chronic Grief); high pre-loss depression that continues after the loss (Chronic Depression); and high pre-loss depression that declines significantly following the loss (Depressed-Improved) (Bonanno, Moskowitz, Papa, & Folkman, 2005; Bonanno et al., 2002; Bonanno, Wortman, & Neese, 2004). As such, even among those who suffered significantly after a loss, clinically meaningful heterogeneity was observed.

While this methodology successfully revealed unique trajectories of bereavement response, it suffered from three serious methodological shortcomings (Bonanno, Westphal, & Mancini, 2011). First, Bonanno et al.'s (2002) approach assessed variability solely in terms of overall sample distribution. The method they used to create the trajectories involved first placing subjects at each time point into high or low depression categories based on their percentile scores on the distribution and then determining change in relation to those cutoffs from before loss to 6 and 18 months after the loss. Unfortunately, relying on a single estimate does not permit this source of variability to influence trajectory designation and can potentially lead to spurious conclusions, as for example in cases when the distribution is not normal (Duncan, Duncan, & Strycker, 2006). Second, Bonanno et al.'s (2002) method of using *a priori* cut points to define trajectories is inherently arbitrary. This approach imposes the change patterns on the data rather than allowing the patterns to emerge directly from the data. Third, the operational definitions for the trajectories were based solely on theoretical assumptions about the nature of the prototypical patterns of variation across time (e.g., Bonanno, 2004) and may not have captured other patterns of response.

Given these limitations, evaluating the resulting trajectory solution is difficult if not impossible in the absence of more sophisticated statistical techniques that might adjudicate among different possible trajectory solutions. An analogous situation would be attempting to assess if variables within a scale cluster together by exploring which variables are most highly correlated. While such a technique provides useful information, it may be inadequate compared to statistical techniques such as factor analysis that are designed to assess latent relationships between variables.

These concerns become even more important as analyses move from elucidating distinct patterns to identifying predictors of those patterns. The rudimentary approach Bonanno et al. (2002) employed did not allow for identification of different parameters of the trajectories (e.g., variability in intercept or slope) and could only identify predictors of the trajectories post-hoc, independent of model building. As we detail below, more sophisticated analytic techniques are now available that can addresses these issues.

Latent Growth Modeling

A number of approaches have been developed to model patterns with high levels of variability. For example, both Hierarchical Linear Modeling (Bryk & Raudenbush, 1987) and Growth Curve Modeling (McArdle & Epstein, 1987) represent advances over traditional linear models because they allow for the exploration and prediction of individual level variability in patterns over time. However, these modeling techniques assume a common pattern that individuals fit better or worse. In situations such as stress responses, for which we find true heterogeneity, such models may be inadequate (Nagin, 1999). A number of methodologies have been developed that better serve this purpose. One such technique, the Nagin Method (Nagin, 1999) has been applied to the study of the course of depression in bereavement (Aneshensel, Botticello, & Yamamoto-Mitani, 2004). A significant advantage of this technique is that it allows for an objective comparison of progressive numbers of distinct trajectories using the Bayesian Information Criteria (BIC) as a point of comparison, where lower scores on the BIC indicate better model fit. This approach also provides information regarding the probability of correct categorization and has provided an empirical demonstration of the significant and meaningful heterogeneity in patterns of depression following bereavement (Aneshensel et al., 2004). Nagin (1999) suggested that a limitation of his technique, however, is that model comparison is limited to the BIC, which can be fallible under certain circumstances, and that advances would require the development of additional methods of evaluating model fit.

A recent set of analytic techniques that has emerged in response to this limitation is Latent Growth Modeling (LGM). Importantly, LGM allows for the empirical exploration of the underlying heterogeneity within the data, which would otherwise be treated as error (Del Boca, Darkes, Greenbaum, & Goldman, 2004), while also providing a number of alternative tests to evaluate model fit (see methods). LGM techniques such as Latent Class Growth Analysis (LCGA) and Latent Growth Mixture Modeling (LGMM) have emerged as particularly strong methodologies for the study of homogeneous trajectories in a larger heterogeneous sample. These techniques test whether the population under study is composed of a mixture of discrete distributions characterized as classes of individuals with differing profiles of growth, with class membership determined by these different growth parameters (Curran & Hussong, 2003). LGM allows for the modeling of longitudinal data with consideration for empirical observation as well as parsimony and interpretability (Jung & Wickrama, 2008), while also allowing for the modeling of covariates as predictors, both of the emergent longitudinal patterns and of latent growth parameters such as class membership, slope, and intercept (Muthén, 2000).

The LGM approach has been applied to a wide variety of phenomena, including drinking behavior among college students (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005), childhood aggression (Schaeffer, Petras, Ialongo, Poduska, & Kellam, 2003), developmental learning trajectories (Boscardin, 2008), disease epidemic (Bonanno et al., 2008), traumatic injury (deRoon-Cassini, Mancini, Rusch, & Bonanno, 2010), life satisfaction in response to interpersonal stressors (Mancini et al., 2011), unemployment (Galatzer-Levy, Bonanno, & Mancini, 2010), childbirth (Galatzer-Levy, Mazursky, Mancini, & Bonanno, 2011), cancer surgery (Lam et al., 2010), and posttraumatic stress following exposure to military deployment (Bonanno et al., in press) and other life threatening events (Galatzer-Levy, Madan, Neylan, Henn-Haase, & Marmar, 2011).

In the current study, we examine prospective trajectories of bereavement from pre-loss to 48 months post-loss using LGM using the same dataset examined by Bonanno et al. (2002). One previous study had also identified trajectories in this dataset through 48 months (Boerner, Wortman, & Bonanno, 2005). However, due to missing data, the sample size for that study was seriously constrained. Because LGM accommodates missing data, however, in the current study we are able to include a larger number of participants from the original dataset. We anticipate that we will uncover heterogeneous patterns of response including resilience, chronic grief, chronic depression, recovery, and depressed-improved, and that the resilient and chronic depression trajectories will remain stable in the more encompassing LGM analyses. The stability of the depressed-improved and the chronic grief class is more questionable, as these patterns have proved more variable in previous studies.