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Review

Machine yearning: How advances in computational methods lead to new insights about reactions to loss

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Abstract
The loss of a loved one is a potentially traumatic event that can result in disparate outcomes and symptom patterns. Machine learning methods offer computational tools to probe this heterogeneity and understand grief psychopathology in its complexity. In this article, we examine the latest contributions to the scientific study of bereavement reactions garnered through the use of computational methods. We focus on findings originating from trajectory modeling studies, as well as the recent insights originating from the network analysis of prolonged grief symptoms. We also discuss applications of artificial intelligence for the accurate identification of major depression and post-traumatic stress, as examples for their potential applications to the study of loss reactions.

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Introduction

Grief over the death of an important person in our lives is a distressing and potentially traumatic event (PTE). Beginning with the very first systematic studies of bereavement [1], researchers have nearly universally assumed that the initial grief experience leads to only two possible outcomes: either a gradual resolution of the initial grief into a more manageable form of integrated grief or a prolonged and pathological form of unresolved grief [2]. Although theories of grieving vary in their conception of the mechanisms that might inform this binary pathway [3], generally it has been assumed that successful resolution of grief requires active engagement, sometimes referred to as 'grief work', on the part of the grieving individual, whereas prolonged grief comes about primarily due to an inability or failure to successfully complete the work of mourning.

Although the characteristics and risk factors leading to pathological bereavement responses have been increasingly studied with empirical methods, this research remains firmly rooted in a similar top-down theoretical framework. Such an epistemic approach has two major shortcomings. First, it heavily downplays rates of psychological resilience after the loss because of its a priori focus on maladaptive responses within clinical samples—in steep contrast to population findings showing most individuals being able to successfully cope to the loss [4]. Second, it produced substantial debates among competing theories attempting to establish the core features of grief-related pathology—to the point of offering conflicting interpretation of the same analytic results [5]. Different theoretic frameworks ultimately resulted in a plethora of alternative diagnostic criteria for a prolonged grief disorder (PGD), which possibly slowed its adoption in psychiatric diagnostic manuals and dissemination to clinicians.

A comparative perspective to the study of grief reactions has emerged with the advent of advances in computational modeling. Although first appearing in relatively primitive form [6], computational approaches to bereavement research have evolved in lockstep with technical advances over the past two decades, developing innovative data science tools to study mental health outcomes [7]. With these advances also came the ability to probe a wide variety of diverse bereavement outcomes and to study their characteristics beyond diagnostic constructs—down to a personalized level. These insights have been achieved by the proliferation of machine learning methods and in particular unsupervised learning approaches, which interrogate data in search for patterns while suspending expectations of predetermined outcomes (other than learning parameters) [8]. Such methods provide the tools to capture population trends and detect symptom clusters, which makes them particularly useful to study heterogeneous reactions to PTEs [9,10]. Importantly, computational approaches are not divorced from theory. Rather, they complement and in some cases expand theory through bottom-up procedures, by probing the validity of both existing and alterative frameworks through emergent findings.

In this review, we elaborate on the recent use of computational methods to address key issues in bereavement. In particular, we focus on unsupervised machine learning. First, we examine findings from latent trajectory modeling studies, which use mixture modeling to tease outcome heterogeneity within large samples after the loss. We then examine recent discoveries captured from network analysis studies, which use graphical lasso models to associate as well as visualize the elements of grief psychopathology and its correlates. Finally, we discuss forthcoming supervised artificial intelligence (AI) approaches. These cutting-edge methods have already offered important contributions in the study of reactions to other PTEs [11] and hold promise in moving the scientific study of reactions to loss toward more empirically grounded theory.

Trajectory modeling

In the early 2000s, longitudinal trajectory research on bereavement research showed that grief outcomes were heterogeneous: some people experienced ongoing, disabling levels of distress, whereas others experienced symptoms that gradually declined, and still others experienced little or no disruption in functioning [6,12]. These findings, however, suffered from methodological limitations as they were based on relatively simple statistical assumptions: trajectories were derived from the overall sample distribution and somewhat arbitrary cut points. The exploration of population heterogeneity became more empirically grounded with the adoption of unsupervised learning approaches. One such approach, latent growth mixture modeling (LGMM) [13], tests whether the sample is best represented by a single response trajectory or several discrete populations, each characterized by a different growth curve pattern [14]. Owing to its computational flexibility, LGMM emerged as a practical methodology to demonstrate population heterogeneity in a wide variety of PTEs [15]. Applications of LGMM to bereavement not only confirmed but also extended and clarified the basic trajectory patterns identified using more basic analytic approaches [16,17]. Although most of the early work on trajectories of grief reactions was conducted using depression symptoms, more recent studies were able to examine trajectories of grief-specific symptoms [18–20]. Across these different samples and measures, the modal reaction to the loss was psychological resilience, with mild to no symptoms, whereas patterns of clinically relevant symptoms emerged only for a fraction of individuals. Both patterns occurred at rates consonant with those observed in response to other PTEs [15].

Because of the lack of consensus on a grief diagnosis, none of the aforementioned studies examined different sets of symptoms, nor how they vary in their capacity to capture adjustment over time. Nonetheless, temporal sensitivity is fundamental for accurately distinguishing culturally appropriate grief from clinically relevant responses. To answer this question, we examined grief trajectories based on clinical interview data from spousal bereavement for both Diagnostic and Statistical Manual of Mental Disorders—5 [21] and International Classification of Diseases—11 [22] grief diagnoses. LGMM symptom trajectories showed that PGD symptoms (from the International Classification of Diseases—11 diagnosis) were more sensitive to changes over time (by capturing a more diverse range of trajectories), as well as better associated with caseness, functioning, and depression [23].

LGMM has also been used to identify elements that account for differences in how grief reactions develop over time. Although no major difference has been identified based on the type of loss [17], recent research showed that gender can account for outcome differences. In another study of spousal bereavement [24], the prolonged grief trajectory captured the largest proportion of probable PGD cases in both genders. However, within prolonged grief, men showed more acute symptoms at baseline, whereas women showed higher likelihood of symptom increase over time. This study suggests that prospective risk factors of bereavement responses can be identified through further analysis of LGMM trajectories in greater detail than overall subgroup delineation.

Network analyses of grief symptoms

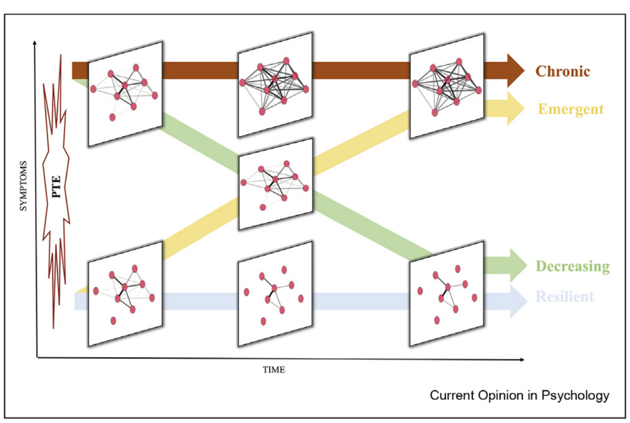
Another example of advancements stemming from computational methods is the use of network analysis. As effective treatments for prolonged grief reactions proliferated [25], the need for a reliable and valid grief diagnosis became imperative. However, debate about what might constitute its core elements was contentious [26]. Network analysis not only provided a useful method to address this problem but also offered a new way to think about psychopathology. It is an emergent approach fostered by the availability of statistical packages able to run its computations [27] (i.e. typically consisting of regularized lasso-penalized partial correlation models). Networks examine psychopathology at the levels of symptoms. Thus, prolonged grief is examined as an interconnected network made by individual symptom interactions [27]. For example, a well-documented symptom interaction observed in grief is the association between yearning about the deceased and emotional pain [28–30]. Loneliness also emerged as a highly interconnected element of grief-related pathology [30,31], which interestingly remains equally important in another type of social disruption, divorce [32].

Beyond studying symptom patterns, network analysis can help identify the most important or central symptoms which, in turn, are likely to foster the development of psychopathology [33]. Stable findings on the structure and centrality of post-traumatic stress disorder (PTSD) [34] and major depression [35] symptoms have emerged across multiple cross-sectional studies. Similar exploratory work on the structure of grief psychopathology is underway. Analyses of multiple samples show yearning and emotional pain to be strongly central elements of grief pathology [28–30], confirming their status as core symptoms. A more surprising and emergent result showed meaninglessness and role confusion to be strongly central elements [30,36]. Consistently, meaninglessness was strongly associated with differences in quality of life [37], and changes in worldview are associated with personal growth after the loss [38]. These findings demonstrate the importance of thinking of grief pathology as a complex system, rather than a diagnostic construct. An even more nuanced understanding of the causal development of prolonged grief will likely emerge from temporal networks based on ecological momentary assessments [39].

Combining trajectories and networks

A promising but as yet untested approach involves the combination of longitudinal modeling and network analysis. The possibility for such an integration comes from recent work based on dynamical latent variable modeling, in which networks are created from longitudinal 'snapshots' of data [40] (see Figure 1). This approach has been suggested as a solution to tackle heterogeneity within network analysis [41], which otherwise considers the sample under analysis as homogeneous. Proof of concept combining networks and latent growth has been shown to tease networks over time in a large development cohort [42]. Dynamical latent variable modeling also allows integration of trajectories with networks by producing separate networks for the different subpopulations previously identified via LGMM. The ability to compare symptom patterns between populations with different outcomes may offer compelling insights on the mechanisms through which grief pathology develops (e.g. chronic symptom vs. remitting symptom networks).

Figure 1



Trajectory and network models as computational approaches to study reactions to loss and to other potentially traumatic events (PTEs).

Artificial intelligence and the road ahead

Further opportunities for computational investigations of grief come from recent advances in AI-driven approaches. These methods capture high-dimensional nonlinear relationships that can associate different information levels (e.g. biological, multiomics) with mental health outcomes [11]. In a recent study, a deep neural network model accurately associated polygenic risk scores with prospective bereavement outcomes over six years (along other PTEs), as identified through LGMM [43]. In another study, LGMM trajectories of PTSD symptoms over one year were accurately predicted from biological and psychological variable captured at the initial ER visit (immediately after the PTE). The algorithm for this model was also externally validated in an independent sample of trauma survivors from an independent emergency trauma center [44].

Beyond their use in more sophisticated analyses, AI-derived methods including computer vision and natural language processing hold tremendous promise as empirical markers of mental health status. Algorithms have the ability to objectively discriminate elements that represent symptoms, including facial expressions, voice prosody, affect, psychomotor traits, and conversational sentiment [8]. Recent developments show that both PTSD and depression [45,46] can be algorithmically detected through the analysis of raw multimedia data. Conversational analysis has also been used to identify levels of suicidal thoughts and behavior [47], symptoms of particular relevance to grief-related pathology [23]. Given the similarities in outcome patterns between different PTEs [15], we believe that combined visual, speech, and linguistic analysis could successfully improve the empirical quality of the study of grief reactions.

Conclusions

This review examined some of the most important trends in computational approaches to bereavement. We primarily focused on trajectory and network modeling studies, as well as the latest advancements in AI in their role to detect, tease, and conceptualize patterns across populations and symptom data. Importantly, we are not advocating that the field should flatten into a data mining venture, as the specific characteristics of samples and of the analytic models can still strongly influence study outcomes. There is a garden of forking paths behind every analytic model, and any methodology can influence results as much as theory [48]. Nevertheless, we believe that computational approaches have the advantage of transparency, given their data-driven nature and the ability to share analytic codes and methods. These characteristics meet the fundamental requirements needed to improve replicability in science, offering insights on grief that are clear and can be re-evaluated in multiple groups and contexts. Given these considerations, we believe that embracing computational methods is an important step to make our field as scientific as possible, with the ultimate goal of providing treatment and informing policies that are firmly rooted in data.

Conflict of interest statement

Nothing declared.

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