Transactional Relations Between Emotion Regulation and Adjustment in Caregivers of Children Diagnosed with Cancer

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Abstract

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Emotion regulation (ER) is a trans-diagnostic factor that has increased understanding of etiology and treatment models for psychopathology, including depression and anxiety disorders. Despite the growing body of research suggesting that deficits in ER are associated with psychopathology, little is known about the temporal relations between these variables. Although ER has often been conceptualized as a risk factor for psychopathology, research in this area has been predominantly correlational and limited the knowledge of whether ER is a predictor, concurrent marker, or consequence of psychopathology. Studying temporal relations between ER and psychopathology can yield insights into how ER contributes to the development and maintenance of psychopathology, particularly for groups of individuals at risk for mental health problems. One such at risk group is caregivers of children with cancer, who show significantly increased levels of depression and anxiety during the first year following the child's diagnosis. Caregivers of children with cancer also experience ongoing stress beyond the initial shock of the diagnosis, including an increased need for regulating a variety of difficult emotions during their child's treatment. In addition to being at risk for increased symptoms of psychopathology, caregivers of children with cancer also show decreased physical health, and many experience high levels of treatment related stress witnessing their child go through intensive treatment. Little work to date has examined how ER efforts in parents of children with cancer is associated with parental psychopathology, treatment related stress, and physical health during this period.

The present study addresses limitations in the current research by first testing a measurement model of ER, and then examining associations between ER and adjustment in caregivers of children with cancer over the first year following diagnosis. Specifically, the study investigates a transactional model of ER and adjustment, with emphasis on assessing temporal relations among these factors. Participants consisted of 159 caregivers of children newly diagnosed with cancer who participated in a larger prospective study. Caregivers completed self-reports of their ER, psychopathology, treatment related stress, and physical health at diagnosis, 6 months post-diagnosis, and 12 months post-diagnosis. Caregiver ER was measured using the Parent's Response to Stress Questionnaire (RSQ), and psychopathology was measured using the Center for Epidemiological Studies Depression Scale–Revised (CESD-R), the Impact of Events Scale–Revised (IES-R), and the Depression, Anxiety, and Stress Scale (DASS). Treatment related stress was assessed using the Treatment-Related Events Questionnaire (TRE), and caregivers reported on their physical health using the Caregiver Health Survey (CHS).

Results supported a two factor measurement model consisting of adaptive secondary control engagement (SCE) ER strategies and maladaptive disengagement (DIS) ER strategies. Cross lagged models showed uni-directional relations between SCE and adjustment, with higher rates of psychopathology and treatment related stress prospectively predicting lower use of SCE. In contrast, higher DIS prospectively predicted higher psychopathology. Additional unexpected effects showed that better physical health prospectively predicted lower use of SCE strategies, and higher rates of psychopathology and treatment related stress prospectively predicted less use

of DIS. Latent change score (LCS) models aimed at assessing dynamics of change between these factors were not successfully estimated using the current data.

The current study expands on previous ER literature by showing divergent longitudinal effects between adaptive and maladaptive ER strategies with adjustment in a high risk sample of caregivers of children recently diagnosed with cancer. This study highlights the importance of ER as both a transdiagnostic predictor, as well as outcome, in relation to important markers of caregiver well-being, including psychopathology, treatment related stress, and physical health. Findings support the utility of addressing ER during prevention and intervention efforts aimed at fostering resilient outcomes for families with a child who has cancer. Implications and directions for future research in ER and pediatric cancer is highlighted.

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CHAPTER 1 | Introduction

Background

Emotion regulation is a transdiagnostic factor that has received considerable research attention in the study of psychopathology, including the two most prevalent mental health problems of depression and anxiety (Aldao, Nolen-Hoeksema, & Schweizer, 2010; Kring & Sloan, 2010; McLaughlin, Mennin & Farach, 2007). Emotion regulation (ER) refers to how people influence, control, experience, and express their emotions (Gross, 1998). A rich and diverse literature on this subject has identified important ways in which our responses to emotions modify our emotional experiences, expressions, behaviors, and physiological states, thereby increasing or decreasing the likelihood of psychopathology (Campbell-Sills, Barlow, Brown, & Hofmann, 2006; Gross, 1998; Hofmann, Heering, Sawyer, & Asnaani, 2009).

Aldao, Nolen-Hoeksema, & Schweizer's (2010) review of ER and its associations with a range of mental health outcomes found that ER shows particularly strong links with symptoms of depression and anxiety. In general, depressed and anxious individuals show differences in their ability to select and implement effective ER strategies, report significantly worse expectancies about the effectiveness of their regulation efforts, and show poorer outcomes of ER efforts compared to healthy controls (Campbell-Sills, Ellard, & Barlow, 2014; Joorman & Siemer, 2014). Despite the growing body of research on ER in depression and anxiety disorders, as well as the increased focus on ER in psychopathology treatment models (Kring & Sloan, 2010; Linehan, 1993), significant gaps remain in this literature. One question that remains unclear is the nature of temporal relations between ER and psychopathology. That is, does ER function as a risk factor for, an epiphenomenon of, or consequence of depression and anxiety disorders? Given the cross-sectional nature of most of the current research, as well as the methodological challenges of studying ER and psychopathology (see Bloch, Moran, & Kring, 2010), an understanding of temporal associations between ER and psychopathology symptoms is limited.

Models of depression and anxiety increasingly incorporate ER as a core process underlying its etiology and treatment, and there is a need to identify and strengthen our understanding of the temporal relation between ER and psychopathology. Uni-directional models of ER as a trans-diagnostic risk factor for mental health outcomes may oversimplify the nuanced relationships between these factors, thus limiting the usefulness of such trans-diagnostic research and theories. Longitudinal research that tests more complex transactional relations can inform and strengthen ER-targeted conceptualizations and treatments for depression and anxiety disorders. Furthermore, understanding how ER and depression and anxiety symptoms progress over time can enhance our knowledge of functional relations between ER and major mental health outcomes in at risk individuals.

Uni-directional models suggest two possibilities for understanding the associations between ER and depression. The first is that ER is a preceding risk factor for later psychopathology. This theoretical framework implies that ER is an individual difference characteristic that precedes and predicts the later likelihood of depression or anxiety symptoms. An alternative explanation is that the onset of psychopathology may be associated with later changes in ER abilities (Katz & Gurtovenko, 2015; Gurtovenko & Katz, 2017). For example, an individual who is already prone to experiencing distressing levels of anxiety or depression may also experience high levels of intense emotions and be too overwhelmed to select and adaptively apply effective ER strategies. Pre-existing anxiety and depression symptoms may lead individuals to later develop and maintain a reliance on less effective ER strategies over time (Campbell-Sills, et al., 2014).

Yet another way to conceptualize the relationship between ER and psychopathology is to look beyond uni-dimensional main effects models and examine the likelihood that these two factors influence one another in a more nuanced way over time. There is emerging evidence, primarily found in research on adolescence, to suggest a more complex and ongoing transactional relation between ER and depression and anxiety (Nolen-Hoeksema, Girgus, & Seligman, 1992; Nolen-Hoeksema, Stice, Wade, & Bohon, 2007). This research suggests that there may be a reciprocal process occurring, whereby ER contributes to the development of psychopathology, which increases risk for later maladaptive ER, which then further increases risk for psychopathology down the line. Further research investigating the validity of such dynamic inter-relations between ER and psychopathology, particularly in populations that are at risk of psychological adjustment difficulties, has potential to advance questions of basic science and clinical applications related to the regulation of emotion.

The current study proposes and empirically tests a transactional model of ER and psychopathology (depression, anxiety, PTSS) in a sample of caregivers of children with pediatric cancer over the first year following diagnosis. This sample and time period is a useful context in which to study relations between ER and adjustment, given that caregivers of children diagnosed with cancer show significantly increased levels of depression and anxiety during the first year following the child’s diagnosis (Katz et al., 2018; Pai et al., 2007). Caregivers of children with cancer experience ongoing stress well beyond the initial shock of the diagnosis, including an increased need for regulating a variety of difficult emotions (Kazak et al., 2005; Sloper, 2000; Van Dongen-Melman et al., 1998; Wijnberg-Williams, Kamps, Klop, & Hoekstra-Weebers, 2005). In addition to being at risk for increased symptoms of psychopathology, caregivers of children with cancer also show decreased physical health (Klassen et al., 2008; Tsai et al., 2013), and many experience high levels of treatment related stress witnessing their child go through intensive treatment (McCaffrey, 2006; Stuber et al., 1997). Thus, we also examine transactional patterns of ER and factors of physical health and treatment related stress, with the goal of investigating whether ER may also be related to these other important adjustment factors. Studying the patterns of relations between ER and psychological and physical health outcomes in this at risk group has potential to improve assessment, prevention, and intervention with caregivers of children with cancer.

We will first review relevant research on conceptualizations of ER and psychopathology, along with discussion of a handful of prospective longitudinal studies that begin to inform temporal associations between these factors. Next, prior work on ER and psychopathology, specifically in caregivers of children diagnosed with cancer is reviewed. We then review similarities and differences between ER and the closely related construct of coping, as well as examine the literature on coping and psychological adjustment in caregivers of children with cancer as it informs questions in regard to ER. Finally, we explore caregiver physical health and treatment related stress as other important markers of wellbeing that are worthy of study in this population, discuss how ER may be implicated, and present the current study aims.

Emotion Regulation

Emotion regulation refers to the processes through which individuals influence which emotions they experience, when they experience them, and how emotions are experienced and expressed (Gross, 1998). ER has been conceptualized and studied as a multifaceted process that includes experiential, behavioral, and physiological components (Gross, 2014; Thompson, 1994). Much of prior research and theory in this area has been driven by a strategy-based model of ER, which conceptualizes ER according to the characteristics and correlates of specific ER strategies

(Naragon-Gainey, McMahon, & Chacko, 2017). From this perspective, ER has been most commonly characterized as falling into a set of six strategies or responses, three of which are considered to be adaptive and three considered to be maladaptive.

Early operational definitions of adaptive ER strategies, such as reappraisal and problem solving, emerged from the stress and coping literature (Carver, Scheier, & Weintraub, 1989; Folkman & Lazarus, 1986) and cognitive-behavioral conceptualizations of depression and anxiety (Beck, 1976; Marlatt, Baer, Donovan, & Kivlahan, 1988). According to Gross (1998), the ER strategy of reappraisal functions to decrease negative emotions by placing a neutral or positive interpretation on a potentially stressful event. Similarly, the ER strategy of problem solving is also understood to have positive effects on emotions and behavioral outcomes. Identifying an effective solution to the emotion eliciting stimulus and consciously taking steps towards this solution can decrease negative emotion and is related to better overall psychological adjustment (Aldao, Nolen-Hoeksema, & Schweizer, 2010). More recently, mindfulness based therapies have also introduced the value of non-judgmental acceptance, or the allowing of uncomfortable experiences without fighting them, as an effective ER strategy (Linehan, 1993; Hayes et al., 1999).

Maladaptive ER can be characterized by both a lack of effective ER strategies as well as an ER repertoire high in ineffective strategies. Ineffective ER strategies such as suppression and avoidance have been found to be implicated in the role of adjustment outcomes including anxiety and depression (Hayes et al., 1999; Wegner & Erber, 1992; Wegner & Zanakos, 1994). Suppression of emotion is associated with an increase in the presence of an unwanted experience and is related to heightened physiological experiences of emotion (Wegner, Broome, & Blumberg, 1997). Avoidance of negative or uncomfortable emotion is also a significant contributor to psychopathology by maintaining maladaptive behaviors in the long run and keeping an individual from taking necessary actions towards resolution (Hayes et al., 2004). Another maladaptive ER strategy that has been widely studied in the literature is rumination, which is the tendency to repetitively focus on a negative experience of emotion and its causes and consequences (Nolen-Hoeksema et al., 2008; Watkins, 2008). Rumination is believed to interfere with problem solving and other effective responses, and ultimately keeps a person stuck in a depressive or anxious state while limiting their flexibility and capacity to respond adaptively (Ward, Lybumorsky, Sousa, & Nolen-Hoeksema, 2003).

Emotion Regulation, Depression, & Anxiety

ER has been predominantly studied from a mental health perspective, and is increasingly incorporated into models of psychopathology (Linehan, 1993; Campbell-Sills & Barlow, 2007; Barlow et al., 2010; Kring, 2010). Given that anxiety and depression are two of the most prevalent and commonly comorbid mental health problems in the general population (Kessler et al., 2009; Brown, 2001), it is not surprising that ER has been frequently examined as a trans-diagnostic factor in the context of these disorders. Aldao et al.'s review (2010) of ER across a range of psychopathology found that ER strategies show particularly strong relations with symptoms of depression and anxiety. Although distinctly different disorders, individuals experiencing both anxiety and depression have high levels of negative emotion (Werner & Gross, 2010), and features of both disorders can be conceptualized as unsuccessful attempts in managing unwanted emotions (Campbell-Sills & Barlow, 2007). There has been considerable correlational research to date that has informed the ways in which difficulties in regulating emotions may be related to experiences of anxiety and depression. Although a complete examination of this literature is beyond the scope of the current study, a brief overview of relevant findings regarding the relation between ER and anxiety and depression follows.

Individuals with anxiety disorders experience a range of difficulties in domains of ER and emotional experiences in general (Ehring & Quack, 2010; McLaughlin et al., 2007; Mennin et al., 2005, 2009, Salters-Pedneault et al., 2006; Tull & Roemer, 2007; Weiss et al., 2012). For example, individuals with Generalized Anxiety Disorder (GAD) show poorer understanding of emotions, higher negative reactivity to emotions, and decreased abilities to self-soothe compared to non-anxious individuals (Mennin, Heimberg, Turk, & Fresco, 2005; Tull, Stipelman, Salters-Pedneault, & Gratz, 2009). Campbell-Sills, Ellard, & Barlow's (2014) overview of ER across anxiety disorders posited several specific ways in which problems with ER manifest in individuals with anxiety disorders compared to those without anxiety. They suggest that anxious and non-anxious individuals primarily show differences in their ER strategy selection, ability to implement strategies, evidence of divergent effects of ER between the groups, and differences in neurobiological characteristics related to ER. A considerable amount of correlational study findings converge to support the notion that ER is a trans-diagnostic feature that distinguishes individuals with anxiety from non-anxious controls (Campbell Sills, Ellard, Barlow, 2014).

Similar to anxiety, depression can be understood as ineffective attempts to regulate emotions (Gross & Munoz, 1995; Campbell-Sills & Barlow, 2007). Individuals with depression show difficulties in identifying emotions (Honkalampi, Saarinen, & Hintikka, 1999; Rude & McCarthy, 2003) and being accepting and tolerating of negative emotions (Brody, Haaga, Kirk, & Solomon, 1999; Campbell-Sills, Barlow, Brown, & Hofmann, 2006). Joorman & Siemer (2014) have suggested that there are two distinct ways in which depression and ER are related. First, depressed individuals may show differences in their strategy selection and expectancies about the strategies they use compared to non-depressed individuals. Second, there may be more difficulties in successfully implementing useful ER strategies, such as reappraisal, among depressed individuals compared to their non-depressed counterparts (Joorman & Siemer, 2014). Thus, similar to considerable research suggesting relations between anxiety symptoms and impaired ER, correlational findings also suggest that depressed individuals also struggle in their abilities to regulate emotion.

Temporal Associations Between ER, & Psychopathology

There is compelling evidence to date which supports ER as a transdiagnostic factor underlying anxiety and depression. Unfortunately, much of this work is cross-sectional in nature and does not lend insight into the question of temporal directionality between ER and psychopathology. Although it is clear that ER and anxiety and depression are closely associated, it is yet to be determined whether this is due to ER functioning as a risk factor for, a co-occurring marker of, or a consequence of symptoms of psychopathology. This question represents a significant gap in our knowledge regarding the causal and functional relationship between ER and psychopathology.

Psychological theories and conceptualizations between variables of interest, including those regarding ER and psychopathology, often describe processes that unfold over time (Ferrer & McArdle, 2010). Without specifically testing temporal dynamics, there are several distinctly different possibilities about the predictive relation and co-development between ER and psychopathology that may exist. For instance, a non-anxious individual's failure to select and successfully implement adaptive ER strategies may be the precursor to developing anxiety over time. Alternatively, an individual who is already prone to experiencing distressing levels of anxiety may also experience high levels of intense emotions and be too overwhelmed to select and adaptively apply more cognitively rigorous (but effective) strategies such as reappraisal. Instead, already anxious individuals may develop and maintain a reliance on less effective strategies like suppression over time (Campbell-Sills, et al., 2014). The correlational work on depression shows the same questions and methodological challenges; that is, markers of impaired ER are observed in already depressed individuals and it is difficult to disentangle which appeared first. As noted by Joorman & Siemer (2014) in regards to research on depression and reappraisal, this “makes it difficult to examine whether decreased reappraisal use is a symptom of depression or indeed a risk factor.” (pg. 417).

Given that models of depression and anxiety increasingly incorporate ER as a core process underlying its etiology and treatment, there is a need to identify and strengthen our understanding of the temporal relation between ER and psychopathology. Unfortunately, there are few prospective longitudinal studies to inform the question of whether ER is a precursor to, an epiphenomenon, or a consequence of depression and anxiety symptoms. There exists a small body of longitudinal evidence to support the notion that ER acts as a risk factor that precedes the onset of depression and anxiety. A bulk of this research has come from studies that utilized the same large diverse group of 6^{th}-8^{th} grade adolescents from a small urban community in central Connecticut (McLaughlin, Hatzenbuehler, Mennin, & Nolen-Hoeksema, 2011; McLaughlin & Hatzenbuehler, 2009; McLaughlin, Hatzenbuehler, & Hilt, 2009; Hatzenbuehler, McLaughlin, & Nolen-Hoeksema, 2008; Michl, McLaughlin, Shepherd, & Nolen-Hoeksema, 2013). Prior relevant research with other samples has also focused on adolescents, with only 2 studies to our knowledge that have examined ER and psychopathology over time in adults (McLaughlin et al., 2010; Michl et al., 2013).

When studies have moved beyond conceptualizing the relation as uni-directional, they have found that ER and psychopathology may show a transactional influence on one another over time. This process has been observed in youth in regard to depression and ER (Burwell & Shirk, 2007; Nolen-Hoeksema, Stice, Wade, & Bohon, 2007; McLaughlin, Hatzenbuehler, & Phil, 2009). For example, Nolen-Hoeksema, et al., (2007) found that rumination predicted increases in later depressive symptoms, and depressive symptoms predicted future increases in rumination in adolescents assessed annually over six years. McLaughlin, Hatzenbuehler, & Phil (2009) showed that baseline (T1) anxiety and depression symptoms were both predictive of ER four months later (T2), which subsequently predicted symptoms three months after that (T3). Similarly, Burwell & Shirk (2007) found that adolescent depression predicted significant increases in rumination assessed 6-8 months later, which then predicted increased depression 6-8 months after that.

These findings also extend to work with adults (McLaughlin & Nolen-Hoeksema, 2011), showing an ongoing transactional relation between depression and rumination. McLaughlin & Nolen-Hoeksema's (2011) work with an adult sample found that baseline anxiety symptoms predicted increases in rumination one year later, with rumination also being related to increases in later depression. In addition, support for a transactional relation is beginning to emerge in regard to PTSD and ER (Bardeen, Kumpula, & Orcutt, 2013), suggesting that pre-existing PTSD symptoms predispose individuals to maladaptive ER abilities in the wake of new traumatic events, and these ER difficulties predict later adjustment. These few longitudinal studies begin to suggest a transactional relation between ER and psychopathology, and more work is still needed to further test bi-directional influence and temporal dynamics among these factors.

The question of temporal relations between ER and psychopathology is relevant from both a basic science as well as applied perspective. Correlational work suggests that depressed and anxious individuals show differences in their ER strategy selection, success of ER implementation, and effectiveness of ER strategy outcomes compared to healthy controls (Campbell-Sills, Ellard, & Barlow 2014; Joorman & Siemer, 2014). But are individuals who learn to select ineffective strategies placing themselves at risk for later development of psychopathology? Or do depressed and anxious individuals increasingly rely on ineffective strategies because they are anxious and/or depressed? A transactional model would suggest that both processes are occurring. This implies a cycle where risk factor (ER) exacerbates psychopathology, which in turn exacerbates the risk factor that further maintains the psychopathology. Uni-directional linear models of causation, where static symptoms and traits are assumed to respond in consistent ways to the influence of risk factors, may not fully explain the nuanced trajectories of psychopathology over time (Hinshaw, 2013). A shift to conceptualizing and studying transactional relations between ER as a trans-diagnostic factor and anxiety and depression outcomes will yield more insight and specificity into the relation between these factors across development.

ER, Psychopathology, & Caregivers of Children with Cancer

Studies show that a significant percentage of parents of children with cancer experience considerable distress during and after their child’s treatment (Brown et al., 1993; Kazak et al., 2005; Sloper, 2000; Van Dongen-Melman et al., 1995; Wijnberg Williams, Kamps, Klop, & Hoekstra Weebers, 2006). Reviews of empirical literature on caregiver adjustment in pediatric cancer suggest that caregivers are at significantly increased risk for experiencing a wide range of difficulties, including heightened levels of mental health consequences like depression and anxiety (Grootenhuis & Last, 1997; Patenaude & Kupst, 2005). For example, Brown et al. (1993) reported that 34% of mothers of children at various stages of treatment for leukemia qualified for a diagnosis of at least one psychiatric disorder. Furthermore, many of these mothers (23.3%) met criteria for two disorders, with high rates of anxiety disorders (e.g., generalized anxiety disorder, panic disorder) comorbid with a mood disorder (e.g., major depressive disorder, dysthymic disorder).

Caregiver distress peaks around the time of diagnosis and early treatment, and steadily decreases as a function of time (Kupst et al., 1995; Pai, 2007). Several reviews have suggested that caregiver distress often decreases to normative levels in the course of the first year following diagnosis (Grootenhuis & Last, 1997; Patenaude & Kupst, 2005). However, not all caregivers of children with cancer show heightened levels of psychopathology, and considerable variability within and between studies exists (Sloper et al., 2000). Some subgroups of caregivers show resilience following the stress of their child's cancer (Brown et al., 1992), while others may develop longer term maladjustment. For example, recent research suggests that up to about 30% of caregivers remain in a clinically distressed range at 1 year after the diagnosis of their child's illness (Katz et al., 2018). Further research is needed to identify factors that help us identify which groups of caregivers are at risk for maladjustment.

Understanding what contributes to the development and maintenance of psychopathology in caregivers of children with cancer is needed given that parental psychopathology is a factor that also significantly increases children's risk for maladjustment (Brown et al., 1993; Lewis & Miller, 1990). Caregiver psychopathology can also lead to significant strain for the rest of the family, including siblings and other family sub-systems (Long & Marsland, 2011; Pai et al., 2007). Thus, it is important to advance knowledge about what factors are associated with mental health outcomes in caregivers of children with cancer, to support the wellbeing of both the caregivers, the diagnosed child, as well as the rest of the family for whom the illness poses significant stress.

There may be individual difference characteristics of caregivers of children with cancer that can help identify which subgroups of individuals recover, and which go on to a more prolonged course of distress following the diagnosis. One such characteristic may be the caregiver's ability to regulate emotion. To this point there has been very little work examining ER and psychopathology in caregivers of children with cancer. Greening & Stoppelbein (2007) conducted the only study to date which has examined these factors in this population, and found that parents of children with cancer who reported more use of social support based ER strategies showed fewer anxiety symptoms. Parents who relied more on avoidance and self-blame strategies for regulating emotion reported higher symptoms of depression, anxiety, and PTSD. Thus, there appear to be ER strategies that are correlated with worse adjustment in this population. More work is needed to further understand the nature of the relationship between ER and psychopathology in caregivers of children with cancer, and how these factors may unfold over the course of the child's diagnosis and treatment.

Other relevant work in parents of children with cancer has examined relations between caregiver psychopathology and the broader but closely related construct of coping (Lazarus & Folkman, 1984). Although coping and ER are not synonymous constructs, they share considerable similarities in their definition, conceptualization, measurement, and application in prevention and intervention of mental health problems (Compas et al., 2014; Compas et al., 2017). Thus, next we review this area of research as it can inform questions of psychopathology and adjustment in caregivers of children diagnosed with cancer, with respect to ER.

Emotion Regulation & Coping

Given that early operational definitions of ER strategies emerged from the stress and coping literature (Carver, Scheier, & Weintraub, 1989; Folkman & Lazarus, 1986), it is not surprising that there is considerable overlap between the construct of ER and coping. Compas and colleagues (2014) have written a review and discussion on this topic, and highlighted important points of convergence and divergence between these constructs. What follows is a summary of this work and other research regarding the conceptual and empirical overlap between ER and coping, and the relevance of this discussion to the current study.

Definitions of ER and coping. Coping and ER have both historically had evolving definitions which researchers have worked to refine and solidify over time (Compas et al., 2014; Compas et al., 2017; Compas, Jaser, & Benson, 2009). The most commonly cited definition of coping comes from the early work of Lazarus & Fokman (1984), which defines coping as "constantly changing cognitive and behavioral efforts to manage specific external and/or internal demands that are appraised as taxing or exceeding the resources of the person" (p. 141). Following the classic early definition of coping, Compas et al. (2001) later defined it as "conscious volitional efforts to regulate emotion, cognition, behavior, physiology, and the environment in response to stressful events or circumstances" (p. 89). More recently, Lazarus' (2006) definition suggested that coping consists of "efforts to manage adaptational demands and the emotions they generate" (p. 10). Common features of these definitions suggest that coping is comprised of intentional and effortful cognitive and behavioral reactions in response to the experience of stress. Compas et al. (2014) highlight the important distinction that coping does not happen under normative daily living conditions, but always occurs in response to stress. Another important distinction that coping theorists have typically agreed on is that it is an effortful (rather than an automatic) process. That is, coping is controlled, purposeful, conscious, and goal-directed behavior.

A frequently cited definition of ER is that of Thompson (1994), who defined ER as “the extrinsic and intrinsic processes responsible for monitoring, evaluating, and modifying emotional reactions, especially their intensive and temporal features, to accomplish one’s goals” (p. 27-28). Building on this early definition, Gross (1998) further described ER as “the process by which individuals influence which emotions they have, when they have them, and how they experience and express these emotions” (p. 275). Another definition provided by Eisenberg, Hofer, and Vaughn (2007) states that ER consists of “processes used to manage and change if, when, and how (e.g., how intensely) one experiences emotions and emotion-related motivation and physiological states, as well as how emotions are expressed behaviorally” (p. 288). Common features of these definitions suggest that ER is concerned with reactions to specific emotions (both positive and negative emotions), and that it refers to an individual’s efforts to up- or down-regulate emotions in the service of accomplishing a goal (Compas et al., 2014).

Compas and colleagues (2014) suggest that conceptual definitions of ER and coping share several important elements in common. 1) ER and coping are both regulatory processes. When individuals engage in ER or coping, they are attempting to regulate or control something about their experiences or reactions. 2) ER and coping can both be characterized by controlled, intentional and purposeful efforts. Although there are automatic processes involved in responses to stress, coping consists of responses that are consciously enacted in the service of a particular goal (Compas et al., 2001). Likewise, although ER has been conceptualized as a continuum which includes automatic processes, it is predominantly characterized by explicit, conscious, and controlled efforts of regulation (Gross, 2013). 3) Given that ER can occur under conditions of stress as well as non-stressful conditions, Compas et al. (2014, 2017) suggest that coping can be thought of as a special case of emotion regulation under stress. Therefore, when ER is occurring under stress, whether an individual is engaging in coping or emotion regulation may be indistinguishable given that "all strategies of emotion regulation can be considered ways of coping" (Skinner & Zimmer-Gembeck, 2007, p. 122). 4) Coping and ER share the common feature of both being processes that unfold and change over time. Individuals can engage in coping and ER in anticipation of a stressor or emotion, during the experience of a stressor or emotion, as well as during periods following stress or emotion.

There are several notable differences between ER and coping as well. 1) One distinguishing feature between ER and coping is that ER includes automatic and non-conscious processes (Gross, 2013), whereas coping does not. Definitions of coping consist primarily of controlled voluntary responses to stress, and distinguish coping from automatic responses to stress such as stress reactivity (Compas et al., 2001; Compas et al., 2014; Compas et al., 2017). 2) Coping always occurs as a response to stress, compared to ER which represents regulation under a broader range of circumstances and in response to a wider range of stimuli (Compas et al., 2001; Folkman & Moskowitz, 2004). ER refers to the regulation of both positive and negative emotions, which may occur under both stressful and normative circumstances (Webb et al., 2012). 3) ER includes both intrinsic (emotion regulated from within the self) and extrinsic processes (emotion regulated by a factor outside the self), whereas coping involves only intrinsic processes. Compas et al. (2012) suggest that although someone might cope by seeking out social support, coping is "only carried out by the person experiencing the stress" (p. 5). In contrast, a mother or early caregiver can help regulate a young child's emotions, and this general concept of co-regulation has received more research attention recently (Butler & Randall, 2013; Gulsrud, Jahromi, & Kasari, 2009). Finally, 4) ER and coping have historically differed in the developmental range across which they are studied. ER has been studied from infancy (Leerkes & Wong, 2012) all the way through to later adulthood (Carstensen, Fung, & Charles, 2003). Coping is typically examined in individuals during late childhood and beyond. This has been in part due to the definition of coping as being a consciously active and intrinsic process. As noted by Compas & colleagues (2014), although younger children experience stress, it is difficult to determine which of their reactions are conscious and intentional, and young children often receive assistance from caregivers to manage stress.

Thus, although ER and coping share many common features, there is also distinct differences in conceptualizations and definitions of the two constructs. At this time, it is difficult to say which construct is broader or whether one construct consistently encompasses the other. In some ways ER captures broader facets of phenomena than coping (positive emotions, non-stress context, automatic, and extrinsic processes), while on the other hand coping covers a broader spectrum of regulation efforts than ER (any volitional non-ER related responses to stress). In cases when emotions are being regulated under a stressful circumstance, ER and coping may be indistinguishable (Compas et al., 2014).

Similarities in measurement of ER & coping. The most common measurement methods employed to assess both ER and coping has been through the use of self-report questionnaires (Compas et al., 2014). The Responses to Stress Questionnaire (RSQ; Connor-Smith et al., 2000) is one of the most commonly used and well validated self-report measures of coping, and Compas and colleagues (2014) have highlighted the fact that the RSQ measures several dimensions of coping, some of which correspond directly with domains of ER. For example, the RSQ contains sets of items that measure cognitive reappraisal using items such as

"I tell myself that things could be worse," and "I think about the things that I am learning from the situation" (Connor-Smith et al., 2000). The ERQ, a widely utilized ER self report measure also taps cognitive reappraisal with items such as "When I'm faced with a stressful situation, I make myself think about it in a way that helps me stay calm," and "When I want to feel less negative emotion, I change the way I'm thinking about the situation" (Gross & John, 2003). Despite slight differences in the wording of the items, it is clear how both measures assess the degree to which an individual changes their thoughts to cope with their emotion or reaction to stress. The RSQ also contains other coping items and subscales which are similarly well matched to some of the most commonly studied ER strategies including emotional suppression, avoidance, rumination, and problem solving (Wadsworth et al., 2004).

Beyond face validity and conceptual similarities of factors measured by the RSQ and those measured by ER measures such as the ERQ, there is evidence to suggest that both constructs behave similarly in regard to their predictive utility. For instance, high cognitive reappraisal as measured in the ER literature is related to lower depression and anxiety (Aldao et al., 2010). Similarly, higher use of secondary control coping strategies, which are a sub-set of coping strategies assessed by the RSQ that include cognitive reappraisal, are related to lower depression and anxiety symptoms (Compas et al., 2006; Jaser et al., 2005). Despite these findings, cognitive reappraisal as measured by the ERQ (ER measure) and RSQ (coping measure) appear to only be moderately correlated (r = .33) (see Andreotti et al., 2013). In regard to emotional suppression as measured in the ER literature, there is evidence to suggest that higher suppression is related to greater symptoms of psychopathology (Aldao et al., 2010). Similarly, primary control coping strategies which include a measure of emotional expression (the conceptual inverse of emotional suppression) are related to lower symptoms of anxiety and depression (Campbell et al., 2009; Jaser & White, 2011).

In summary, coping and ER retain a few distinct features suggesting that they are closely related but unique constructs. On the other hand, the conceptual overlap, similarities in measurement methods, and predictive characteristics in regard to psychological adjustment suggest that they are highly similar. Particularly when conceptualizing and studying coping processes in high stress circumstances such as pediatric cancer, where there is a high need for managing the experience of negative emotion (Klassen et al., 2007; Vrijmoet-Wiersma, 2008), these two constructs may be indistinguishable.

Despite the considerable overlap between constructs of coping and ER, research of these factors has been separate, and this has limited the field's integration of findings from these rich literatures (Compas et al., 2014; Compas et al., 2017). Compas et al., (2017) has proposed that "many of the distinctions between these two constructs are artificial and synthesis of these two lines of theory and research is long overdue" (p. 973). Integrating the theoretical and empirical research between these two constructs can lead to more integrative research and ultimately stronger, more targeted, and comprehensive interventions (Compas et al., 2014).

Coping & Pediatric Cancer

Given the considerable overlap between ER and coping, the dearth of studies examining ER and psychological adjustment in caregivers of children with cancer, and the potential utility of integrating research on these constructs (Compas et al., 2017; Compas et al., 2014), we review the literature on coping and psychological adjustment of caregivers in pediatric cancer to help inform background for the current study questions.

Research with caregivers of children with cancer suggests that individual differences in coping strategies is significantly related to psychological adjustment in this population. Disengagement coping is characterized by cognitive or behavioral avoidance, repetitive wishful thinking, and denial. This style of coping shares strong similarities with the ER strategies of avoidance and rumination. Higher disengagement coping has been found to be significantly related to higher overall negative mental health symptoms in parents of children with cancer (Trask et al., 2003). Primary control coping is characterized by problem solving and well-regulated emotional expression. Prior research has found higher primary control coping to be associated with lower depression symptoms in mothers of children with cancer (Rodriguez et al., 2016). This study also reported observed links between higher secondary control coping, which is characterized by cognitive restructuring much like reappraisal, and lower maternal depression. Compas et al. (2015) examined the relations between coping and depression in both fathers and mothers shortly after their child received a diagnosis of cancer. Their study found that for both mothers and fathers, more use of primary and secondary control coping were related to lower depression symptoms. In addition, more reliance on disengagement coping was associated with significantly higher depression among both parents. These studies highlight that coping responses, often characterized by efforts at regulating and responding to emotions, are closely linked with psychopathology in caregivers of children diagnosed with cancer.

Looking Beyond Psychopathology: Caregiver Health & Treatment Related Stress

Although psychological distress, including high rates of depression and anxiety, are among the most common adjustment difficulties for caregivers of children with cancer, there are also other important outcomes that are worthy of more research attention in this population. One such outcome is a caregiver’s physical health. Qualitative research with pediatric cancer families suggests that negative physical health consequences are one of the most frequently reported effects of caregiving demands on parents (James et al., 2002). Research utilizing quantitative methods also shows that caregivers of children with cancer report significantly worse physical health compared to parents of healthy children (Klassen et al., 2002; Tsai et al., 2013). This is not surprising given that parents of children with pediatric cancer are often called to be ready to provide care to their child at all hours, leaving them little time to attend to their own health needs. Some parents of seriously ill children may neglect their own health given the high demand for caregiving in this context, and more research is needed to identify predictors of which parents are most successful at maintaining their physical wellbeing during this high stress period (Acton, 2002; Klassen et al., 2002).

Another important indicator of caregiver wellbeing in the context of pediatric cancer is the caregiver's experience of treatment related stress. Many caregivers experience high levels of treatment related stress while witnessing their child go through procedures, in response to bad news from providers as treatment progresses, or with worsening prognostic indicators (McCaffrey, 2006; Stuber et al., 1997). General treatment related stress that caregivers may experience while caring for a child with cancer may not be adequately captured by specific measures of depression and anxiety. Assessing this dimension of caregiver well-being is important since families with caregivers who report more treatment related stress also experience potential downstream effects on the adjustment of the diagnosed child as well as other family members. For instance, Pierce et al. (2017) found that caregiver distress predicts worse health related quality of life in children with pediatric cancer. Fladeboe et al., (2018) also found that higher levels of cancer related stress was associated with higher levels of sibling conflict over the first year of treatment.

Measuring broader dimensions of adjustment such as health and treatment related stress in caregivers of children with cancer is in line with a multidimensional view of health, which suggests that psychological symptoms are not the only important indicators of wellbeing (Klassen et al., 2008). More research examining potential predictors and consequences of caregiver physical health and treatment related stress is needed given that these are important dimensions of caregiver adjustment. Moreover, caregiver physical health and treatment related stress can also spill over into adverse negative effects for the family more broadly, and identifying factors that can mitigate such risk processes is needed.

Similar to how ER underlies many forms of psychopathology (Aldao et a., 2010; Kring & Sloan, 2010), research evidence suggests that it may also be significantly associated with medically related stress and physical health outcomes. The relation between ER and physical health symptoms has been studied primarily in samples with medical illness, and this literature suggests that difficulties with ER can exacerbate physical symptoms (Smyth & Arigo, 2009). For example, Burns (2000) found that individuals with chronic pain who show higher use of a repressive coping style, which is similar to the ER strategy of emotion suppression, report higher physical pain. Similarly, the ability to regulate emotion in the context of everyday activities is related prospectively to physical pain symptoms in older adults (Paquet, Kergoat, & Dube, 2005). Better ER abilities are also associated with improved physical pain outcomes in children (Connelly et al., 2011). ER focused interventions also show promising results in regard to their impact on physical health symptoms (Smyth & Arigo, 2009). For instance, Zautra et al., (2008) found that patients with rheumatoid arthritis who received a mindfulness and emotion regulation intervention showed greater improvements in physician-rated joint swelling and tenderness compared to those who received a cognitive-behavioral therapy (CBT) intervention and controls.

Such research leads us to hypothesize that individual differences in ER may be associated with differences in physical health among caregivers of children with cancer, though to our knowledge, this question has not been empirically examined.

Better ER may also be associated with less treatment related stress in other medical populations. Although there are no currently available studies that directly examine relations between ER and treatment related stress in pediatric cancer, evidence from an ER intervention for women with cancer indicated that the ER intervention which focused on emotion awareness and expression, and taught mindfulness based strategies for regulating emotion led to decreased treatment related stress in the form of lower perceived risk of cancer recurrence and lower cancer related worry (Cameron, Booth, & Schlatter, 2007). In addition, more adaptive coping styles and strategies, which are similar to individual differences in ER (see discussion above), have been linked with better health and less illness related stress in medically ill children and their families (Compas & Boyer, 2001). Building on ER as a potential factor that may be associated with treatment related stress as well as physical health in caregivers of seriously ill children may be helpful for identifying another useful point of assessment, prevention, and intervention in this population.

Like the larger literature on ER and psychopathology, the few studies that inform possible relations between ER, health, and treatment related stress cannot disentangle the temporal order between these factors. Although ER is commonly conceptualized as a predictor of health and stress outcomes (i.e., individual differences in ER as a precursor to differences in health and treatment stress), the reverse pattern may be conceptually useful to consider as well. It may be that caregivers who experience improvements in physical health go on to show a higher capacity for adaptive ER. It is also reasonable to assume that if a decrease in treatment related stress occurs, for example following a child's positive treatment response (Tsai et al., 2013), a caregiver's ability to draw on adaptive ER strategies may substantially increase. Thus, we believe it may be useful to examine both concurrent as well as temporal relations between ER and physical health and treatment related stress in this population, insofar as it can better inform the functional relations between these factors over time.

The Current Study

The current study tests transactional relations between ER and adjustment domains of psychopathology, treatment related stress, and physical health in a sample of caregivers of children diagnosed with pediatric cancer over the first year following diagnosis. The following aims were addressed:

Aim 1: Testing a measurement model of emotion regulation. One of the biggest criticisms of the ER literature is the problems and limitations around measurement of this construct (Berking & Wupperman, 2012). Prior psychometric research supports a two factor structure of ER, with factors representing (1) adaptive strategies and (2) maladaptive strategies (Cracco, Van Durme, Braet, 2015; Aldao & Nolen-Hoeksema, 2011). On the other hand, some have suggested that the distinction between adaptive and maladaptive strategies is neither valid nor useful (Kashdan, Young, & Machell, 2015). Thus, an attempt will be made to replicate the two factor adaptive & maladaptive structure, and compare it to a one factor structure that represents a single higher order latent construct of ER.

Aim 2: Comparing uni-directional vs. transactional models of relations between ER and outcomes of psychopathology, treatment related stress, and physical health over time. Towards this aim, cross-lagged path models will be tested using three waves of measurement over the first year following diagnosis. We hypothesize that a model characterized by transactional rather than uni-directional influence will best characterize the relations between ER and adjustment outcomes in this sample. Specifically, we predict that higher use of maladaptive strategies will predict higher rates of psychopathology, higher treatment related stress, and lower physical health, and vice versa, across three waves of measurement during the first year of treatment.

Aim 3: Testing a transactional model of ER and psychopathology, treatment related stress, and physical health by examining dynamics in patterns of change. To test this aim we will use latent change score (LCS) modeling to formally evaluate the sequence of association between ER and adjustment outcomes. LCS models are useful for hypotheses that aim to identify how change in one factor may be a leading indicator of change (or predictor of subsequent change) in another factor (Ferrer & McArdle, 2010). For this final aim, the following questions will be assessed: 1) Is the amount of change in ER related to the amount of change in adjustment outcomes? 2) Is the level of ER at a given time point related to the subsequent amount of *change* in adjustment? (3) Is the level of an adjustment outcome at a given time point related to the amount of subsequent *change* in ER? (4) What are the leading/lagging relations between ER and adjustment outcomes? and (5) What are the leading/lagging relations between *changes* in ER and changes in adjustment?

CHAPTER 2 | Method

Method

Overview

The current study is part of a larger prospective study examining psychosocial adjustment of families with children newly diagnosed with cancer. Primary caregivers of each family recruited for the study participated in a family interaction around the time of diagnosis, two semi-structured Parent Meta Emotion Interviews about their experiences of their own and their child's emotions, and also completed monthly questionnaire packets during the first year after diagnosis. The current study focuses exclusively on a subset of questionnaires that were completed by caregivers at the time of diagnosis (Time 1), 6 months post-diagnosis (Time 2), and 12 months post-diagnosis (Time 3).

Participants

One hundred and fifty-nine families participated in the present study. Children were aged 2-18 (M = 5.6 years, 49% male) and had been recently diagnosed with cancer. Though children 2-10 years old comprised the majority of the sample, 19 adolescents were also included. The majority of children with cancer were identified as White/Caucasian (84.1%) by the primary caregiver, with the remaining identified as Black/African-American (5.6%), Asian (.8%), American Indian (.8%), or other (8.8%). Additionally, 15.1% of participants identified as ethnically Hispanic. In regard to children's diagnoses, the majority of children were diagnosed with leukemia (32.8%), followed by lymphoma (12.6%), sarcoma (10.9%), Wilm's tumor (11.8%), neuroblastoma (5.0%), or another form of cancer (8.4%). The remaining 18.5% of the children were diagnosed with a CNS tumor.

The primary caregiver in most families was the mother (85.5%), with others being a father (12.0%), grandmother (1.7%), and stepmother (0.9%). Primary caregivers were on average 36.41 years old (SD = 7.9). Among caregivers, 78.3% were married, 7.6% were romantically involved but not married, and 14% were not romantically involved. Approximately 1.7% of families reported an annual family income less than \$10,000, 13.0% reported \$10,000 – \$19,000, 8.7% reported \$20,000 – \$29,000, 9.6% reported \$30,000 – \$39,000, 7.8% reported \$40,000 –

$49,000, 5.2% reported $50,000 – $59,000, 7.8% reported $60,000 – $69,000, 5.2% reported $70,000 – $79,000, 7.8% reported $80,000 – $89,000, 7.0% reported $90,000 – $99,000, 19.1% reported $100,00 – $149,000, 4.3% reported $150,000 – $199,000, and 2.6% reported earning greater than $200,000 per year.

Procedures

Participants were recruited as part of a larger study from two children's hospitals in urban areas, and were approached within two weeks following the child's diagnosis. Families were considered eligible if they had a child newly diagnosed with a tumor or cancer who was 2-18 years old at the time of diagnosis, English-speaking, and had no history of developmental delay. Current primary caregivers also needed to be the same primary caregiver as prior to the child's diagnosis. Children with NF1, relapsed cancer, or secondary malignancies were not eligible.

To approach potential families who were being seen on an outpatient basis, providers were asked to briefly introduce the study during a clinic appointment, after which interested families were contacted via phone by a member of the study team. Families were then mailed consent and HIPAA authorization forms. To approach potential families who were inpatients, attending physicians were contacted for permission for the child's nurse to introduce the study to the family. Interested families were then approached by a member of the research team and consent and HIPAA authorization were obtained. Of the 502 families eligible for participation across both sites, 309 were approached, 176 enrolled, with 159 completing at least one study component. Of the families approached who did not enroll, refusal was due to either excessive time required or no reason was given. Data were collected over a twelve-month period beginning with an initial questionnaire packet for each caregiver distributed at the time of consent, followed by monthly questionnaire packets distributed through the mail. If a completed questionnaire packet was not received by the study team within the two-week window for that time point, the packet was skipped and the next month's packet was sent. Primary caregivers completed packets that included measures of the caregiver psychopathology, caregiver treatment related stress, caregiver physical health, and caregiver ER at times 1, 2, and 3 (right after the diagnosis, 6 months post-diagnosis, and 12 months post-diagnosis, respectively).

Measures

Caregiver emotion regulation. The Response to Stress Questionnaire (RSQ; Connor-Smith et al., 2000) is a broader coping measure that was used to measure caregivers' ER. The RSQ includes a list of 11 stressors that pertain to having a child with cancer (e.g. "Not knowing if my child's cancer will get better", "Needing more help and support from family and friends"). Caregivers rated these experiences in terms of how stressful each item had been in the recent past, as well as 57 items that assessed the frequency of a variety of caregivers' responses to such cancer-related stress (on a Likert scale ranging from 0 = not at all to 4 = a lot). The current study used subscales that measured positive ER strategies of cognitive restructuring (e.g., "I think about the things that I am learning from the situation, or something good that will come from it"), problem solving (e.g., "I try to think of different ways to change the problem or fix the situation"), and acceptance (e.g., "I realize that I just have to live with things the way they are"), as well as subscales for negative ER strategies of avoidance (e.g., "I try to stay away from people and things that make me feel upset or remind me of the problem") and rumination (e.g., "When problems with my family come up, I can't stop thinking about how I am feeling"). The RSQ has shown good to excellent internal consistency, test-retest reliability, and construct and criterion validity (Connor-Smith et al., 2000; Wadsworth, Rieckmann, Benson, & Compas, 2004).

Depression symptoms. Symptoms of depression in primary caregivers were measured through self-report using the Center for Epidemiological Studies Depression Scale Revised (CESD-R 10; Radloff, 1977). This 10-item self-report scale asks caregivers to rate the frequency of each symptom within the past month (e.g., "I had trouble keeping my mind on what I was doing"), from 0 (less than 1 day per week) to 3 (5-7 days per week), yielding a total sum score. Sum scores range from 0-30, with higher scores representing more frequent symptoms. Reliability in the current sample was acceptable, with Cronbach's alpha of .84, .86, and .79 at times 1, 2, and 3 respectively, with a mean of .83 across the three time points.

Anxiety symptoms. Symptoms of anxiety in caregivers were measured via self-report using the Depression, Anxiety, and Stress Scale (DASS; Lovibond & Lovibond, 1995). This 21-item questionnaire yields an anxiety sub-score comprised of 7-items assessing frequency of anxiety symptoms in the past month. Items (e.g., "I felt scared without any good reason") were rated 0 (did not apply to me at all), 1 (applied to me to some degree, or some of the time), 2 (applied to me to a considerable degree, or a good part of time), or 3 (applied to me very much, or most of the time). Items are summed to yield a possible total anxiety score of 0-21, with higher scores indicating more frequent symptoms. Reliability in the current sample was acceptable, with Cronbach's alpha of .81, .83, and .74 at times 1, 2, and 3 respectively, with a mean of .79 across the three time points.

Post-traumatic stress symptoms. Post-traumatic stress symptoms (PTSS) in caregivers were measured via self-report using the Impact of Events Scale – Revised (IES-R; Weiss & Marmar, 1995). This 22-item scale assesses three domains of traumatic stress symptoms that map onto the three DSM-IV PTSD criteria: Intrusion (e.g., "Pictures about my child's illness or treatment popped into my mind"), Avoidance (i.e., "I stayed away from reminders of my child's illness”), and Hyperarousal (i.e., “I was jumpy and easily startled “). All items are rated from 0 (not at all) to 4 (extremely), with higher scores indicating a higher level of distress. Each subscale is comprised of a mean of all items in that domain. In addition to subscales, all items are also summed to form an overall symptom severity score ranging from 0-88. The overall symptom severity score was used in the current study. Reliability in the current sample was high, with Cronbach’s alpha of .93, .92, and .94 at times 1, 2, and 3 respectively, with a mean of .93 across the three time points.

Treatment related stress. Stress related to treatment was assessed via primary caregiver report using the Treatment-Related Events Questionnaire (TRE; McCaffrey, 2006). The TRE included questions regarding two main areas of treatment-related stressors: treatment procedures and treatment stressors. For 24 items, the primary caregiver indicated how often each event occurred in their child’s life within the past month (1 = never, 5 = very often), how difficult each event was for the caregiver (1=not at all, 5=extremely), and how difficult the event was for their child (1=not at all, 5=extremely). Of these 24 items, 9 consist of cancer treatment-related procedures (e.g., chemotherapy, lumbar punctures) and 15 consist of treatment stressors (e.g., long hospital stays, uncertainty about the future). The TRE Questionnaire yields Overall Frequency and Overall Difficulty scores for both the caregiver and for the child, which sum across all treatment-related events. The overall difficulty for the caregiver subscale was used in the current study as it measured individual differences in how difficult and stressful caregiver’s experienced their child’s treatment. Reliability in the current sample was acceptable, with Cronbach’s alpha of .89, .94, and .94 at times 1, 2, and 3 respectively, with a mean of .92 across the three time points.

Caregiver physical health. The Caregiver Health Survey (CHS) is a self-report measure used to assess the physical health status of caregivers. The CHS consists of 18 items that measure a range of physical symptoms, changes in overall health, worries about health, and overall health status (E.g., "In the past month, how much have *headaches* been a problem for you?"). Caregivers rate each item on a 5 point likert scale (1 = Extremely problematic, 2 = Very problematic, 3 = Somewhat problematic, 4 = A little problematic, 5 = Not problematic at all). The CHS yields a Total Physical Health score, with higher scores indicating better overall health. Reliability in the current sample was acceptable, with Cronbach's alpha of .86, .81, and .79 at times 1, 2, and 3 respectively, with a mean of .82 across the three time points.

Data Analytic Approach

Aim 1. Testing a measurement model of emotion regulation. This aim was tested using a structural equation modeling (SEM) approach. Analyses were conducted in R using the latent variable modeling package lavaan (Rosseel, 2012). A measurement model of ER using five indicator variables reflecting distinct ER strategies was tested using confirmatory factor analysis (CFA). First, a two factor model consisting of separate factors of adaptive ER strategies (comprised of 3 indicators – cognitive restructuring, problem solving, and acceptance) and maladaptive ER strategies (comprised of 2 indicators – avoidance and rumination) was tested. This measurement model was compared to a one factor model of ER comprised of both adaptive and maladaptive strategies. In addition, measurement invariance of ER across repeated observations was tested within an SEM framework.

The fit of factor structures for ER was assessed using the following fit indices: chi-square, Standardized Root Mean Square Residual (SRMR), Root Mean Square Error Approximation (RMSEA), Akaike Information Criteria (AIC), Bayesian Information Criterion

(BIC), Tucker Lewis Index (TLI), and the Comparative Fit Index (CFI). Several cut score guidelines have been suggested to help guide inferences about poor vs. desirable model fit. NFI, TLI, and CFI values above .90 are considered adequate according to Kline (2006), though .95 and higher are considered to represent a more desirable fit (Hu & Bentler, 1999). RMSEA values below .01, .05, and .08 have been suggested as indicators of excellent, good, and mediocre fit, respectively (MacCallum, Browne, & Sugawara, 1996). An SRMR value of less than .08 is considered a good fit (Hu & Bentler, 1999). AIC and BIC are comparative measures of fit, and were examined as indices of model improvement when comparing nested models (lower values of AIC and BIC indicate relatively better fit).

Aim 2. Testing uni-directional vs. transactional models of relations between ER and adjustment outcomes over time. Aim 2 was tested using a cross-lagged SEM panel design with three waves of measurement through the first year of treatment. A cross-lagged SEM panel model was chosen due to its ability to specify and test interrelations between constructs over time, and compare unidirectional vs. transactional influence between levels of ER and outcomes of psychopathology, treatment related stress, and health. Although cross-lagged models have limitations in regard to assessing change within a construct over time (Rogosa, 1980), they are a useful tool for examining questions concerned with patterns of influence between constructs (Hoyle, 2012; Selig & Little, 2012).

Cross lagged models included the following paths: cross-lagged structural paths, whose regression coefficients reflect the extent to which one construct predicts another (i.e., X_1 predicting Y_2); autoregressive paths, which reflect stability in a single construct over time (i.e., X_1 predicting X_2); and estimates of residual covariance between exogenous constructs, which assesses whether changes in one variable not accounted for by the model are associated with concurrent changes in another. In other words, this assumes that two variables measured simultaneously share at least one unmeasured cause as a function of time (Kline, 2016). Autoregressive and cross-lagged paths are estimated controlling for the other, in other words testing whether one construct predicts variability in another construct over and above what is accounted for by that construct measured at an earlier timepoint (i.e., X_1 predicting Y_2, controlling for Y_1).

To account for missing data, Full Information Maximum Likelihood (FIML) in R was used to estimate model parameters. To test the hypothesis that a transactional relation exists between ER and adjustment outcomes, a baseline model of independence was modeled first that included only autoregressive paths (no cross-lagged paths). The baseline model suggests that constructs of ER and adjustment exist independently and have no relation with one another, and was used as a basis for comparison for subsequent models positing different patterns of relations between variables. Cross-lagged paths were then added in a step-wise fashion to compare three nested models to the baseline model: 1) a model positing a unidirectional relationship from ER to adjustment; 2) a model positing a unidirectional relationship from adjustment to ER; and 3) a bidirectional model incorporating both previous models in which all bidirectional and autoregressive paths were included, representing a transactional relationship between ER and adjustment. Model fit comparisons were done using chi-square difference tests, as well as examination of the Standardized Root Mean Square Residual (SRMR), Root Mean Square Error Approximation (RMSEA), Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC), Tucker Lewis Index (TLI), and the Comparative Fit Index (CFI). If the transactional model results in better fit to the data than the baseline and either unidirectional model, this would support the presence of transactional relations between ER and adjustment outcomes. Path coefficients from the best fitting model are examined to evaluate the strength of influence between ER and adjustment outcomes (and vice versa) over time.

Aim 3. Testing the temporal precedence and dynamics of change between ER and adjustment outcomes. To test this aim, latent change score models were used. Latent change score models (LCS) are a class of SEM models that are used for examining specifications of change over time in single and/or multiple variables. These models are useful for hypotheses that aim to identify how change in one factor may be a leading indicator of change (or predictor of subsequent change) in another factor (Ferrer & McArdle, 2010). What this model yields over and above a cross lagged path model is that it allows one to make hypotheses using *change* of variables of interest as predictors, rather than using just levels at an observed time point as predictors. Moreover, while auto-regressive and cross lagged effects describe between person stability, they do not describe within person stability or change (Selig & Little, 2012). Thus, LCS models are useful for modeling dynamic within person change processes. Specifically, a bivariate latent change score model will model the growth of the two factors using 3 variables: a constant change parameter, a proportional change parameter (describing how each variable influences itself over time), and a "coupling" parameter. This coupling parameter represents the effect of one variable on the consequent changes in the other variable, and is helpful for determining whether the change in one factor tends to lead vs. lag behind the growth of the other factor. Furthermore, LCS models can also allow one to assess temporal order in the changes-to-changes process, for example to predict if recent changes in ER precede changes in future adjustment and vice versa.

LCS models were used to assess the following questions in Aim 3: 1) Is the amount of change in ER related to the amount of change in adjustment? 2) Is the level of ER at a given timepoint related to the subsequent amount of *change* in adjustment? (3) Is the level of adjustment at a given timepoint related to the amount of subsequent *change* in ER? (4) What are the leading/lagging relations between ER and adjustment? and (5) What are the leading/lagging relations between *changes* in ER and changes in adjustment?

CHAPTER 3 | Results

Results

Aim 1: Testing a Measurement Model of ER

This aim was tested using a structural equation modeling (SEM) approach. A measurement model of ER using five indicator variables reflecting distinct ER strategies was tested using confirmatory factor analysis (CFA). First, a two factor model consisting of separate factors of adaptive ER strategies (comprised of 3 indicators – cognitive restructuring, problem solving, and acceptance) and maladaptive ER strategies (comprised of 2 indicators – avoidance and rumination) was tested. This measurement model was compared to a one factor model of ER comprised of both adaptive and maladaptive strategies (see Figure 1).

Before proceeding with substantive analyses, raw ER variables were visually inspected using Q-Q plots to check that there were no significant deviations from normality. No significant deviations from normality were observed for ER variables at all timepoints, and measures of skewness and kurtosis fell within acceptable ranges of normality (skewness and kurtosis values within the +/-1 range) (Gravetter & Wallnau, 2014).

Fit indices for measurement models are displayed in Table 1. The first proposed two factor model (Table 1: Model 1) did not converge, and fit measures were not available, indicating poor fit to the data. The one factor model (Table 1: Model 2) converged, but indicated poor fit to the data according to all fit indices. Correlations between the originally proposed ER subscale indicators were examined to better understand points of misspecification in the original measurement models. With the exception of being unexpectedly positively correlated with Rumination ($r = .24$, $p = .01$), Problem Solving was unrelated to the group of ER indicators and was thus dropped from the measurement model. The one factor model and two factor models were both tested again without Problem Solving as an indicator. This revised two factor model (Table 1: Model 3) still failed to converge, and the revised one factor model's fit (Table 1: Model 4) still failed to demonstrate adequate fit to the data according to all fit indices.

Measurement model re-specifications. Given the poor fit of the originally proposed measurement models tested, a post-hoc exploratory approach was taken to construct a new data driven and theoretically informed measurement model. The aim of the exploratory measurement model development process was to find a theoretically sound and expanded two factor model that would capture a negative and positive dimension of ER. Previous psychometric work using the RSQ (e.g., Wadsworth, Rieckmann, Benson, & Compas, 2004) suggests that most of the ER indicators selected for the current study fell primarily into two categories of coping constructs: 1) secondary control coping (positive strategies characterized by changing how one thinks about and relates to emotions and stress) and 2) disengagement coping (negative strategies characterized by behavioral avoidance and disengagement from painful emotions and experiences). Thus, the originally proposed two factor model of ER was expanded to include the original ER indicators of cognitive restructuring, acceptance, and avoidance, as well as RSQ subscales of distraction, positive thinking, denial, and wishful thinking to include indicators that matched the coping constructs nearest to the originally proposed ER factors in this study. A new model was specified to include a secondary control engagement factor (SCE; cognitive restructuring, acceptance, distraction, and positive thinking) and a disengagement factor (DIS; avoidance, denial, and wishful thinking). This expanded two factor model (Table 1: Model 5) showed significantly improved fit relative to the previous measurement models. Despite the relative improvement in fit, the fit indices still indicated relatively poor fit. Modification indices were examined to assess points of misspecification. Modification indices suggested that a re-specification that included acceptance as a cross loaded indicator on the disengagement factor would lead to the highest increase in model fit (mi = 11.88). Thus, the next re-specified two factor model with acceptance cross loaded on both factors was run (Table 1: Model 6), and this measurement model achieved adequate fit to the data. Factor loading estimates for all indicators were statistically significant, and the cross loaded acceptance indicator estimates suggested that acceptance was making significant contributions to both the secondary control engagement factor as well as the disengagement factor. The structure of this final re-specified expanded two factor model is shown in Figure 2.

Measurement invariance testing. A measure shows measurement invariance (also known as measurement equivalence) across groups if participants with identical levels of the latent construct have the same expected raw score on the measure (Drasgow & Kanfer, 1985). In a repeated measures framework, measurement invariance evaluates the psychometric equivalence of a construct across observations, and indicates that a construct has the same meaning across repeated measures (Putnick & Bornstein, 2016). Thus, whether a scale shows measurement invariance, or to what degree, has strong implications for the interpretation of differences observed using the measure. If measurement invariance can be demonstrated, observed mean differences can be interpreted as differences in the underlying construct between measurement occasions (or groups). If measurement invariance testing fails, it is not possible to assume a stable relation between the latent construct and scale score across measurement occasions, and observed differences in the scale may be due to differences in the underlying constructs, or due to the varying relations between latent constructs and the scores they are comprised of (Hirschfield & Brachel, 2014).

There are four aspects of invariance commonly tested in an SEM framework to assess and establish measurement invariance: 1) *configural invariance*, or assessing equivalence of model form; 2) *metric invariance* (also known as weak invariance), assessing equivalence of factor loadings; 3) *scalar invariance* (also known as strong invariance), assessing equivalence of item intercepts or thresholds; and 4) *residual invariance* (also known as strict invariance), assessing equivalence of item residuals or unique variances (Putnick & Bornstein, 2016). Common methods for testing these domains of measurement invariance in a repeated measures framework consists of specifying a series of model comparisons that define increasingly stringent equality constraints (Hirschfeld, & Brachel, 2014). First, a baseline model is specified in which loading patterns are structurally identical across observations, but the magnitude of all parameters are freely estimated. This model establishes equivalence of the measurement model form across observations. Next, a metric invariance model is specified in which the factor loadings are constrained to be equal across observations. The metric invariance model is compared to the configural model, and if the fit has not significantly worsened it can be assumed that equivalence of factor loadings across observations (weak invariance) has been demonstrated. Third, a scalar invariance model, in which the factor loadings and item intercepts are constrained equal across observations (strong invariance), is specified and compared against the metric invariance model. Again, equivalence of item intercepts across observations is established if the fit of the scalar invariance model does not appear to be significantly worse compared to the metric invariance model. Finally, a residual invariance model, or one in which factor loadings, intercepts, and residual variances are constrained equal across observations (strict invariance), is compared to the scalar invariance model. If there is no significant difference in fit between the scalar and residual model, then it can be said that the measurement shows strict invariance and the residuals and unique variances are equal across observations. Demonstrating invariance at the scalar level is required in order to compare means of latent variables across different groups or observations (Chen, 2008). Demonstrating residual invariance is necessary to establish full factorial invariance, but is not a requisite for examining mean differences on latent factors given that residuals are not part of the latent factor and do not change interpretation of latent mean differences (Vandenberg & Lance, 2000).

Tables 2 and 3 contain chi-square difference tests, fit indices, and a summary of model comparisons conducted to test measurement invariance at the configural, metric, scalar, and residual level for each of the two factors. The SCE factor demonstrated scalar invariance (strong invariance), but failed to demonstrate residual invariance (strict invariance). The DIS factor demonstrated metric invariance (weak invariance), but fell short of demonstrating scalar invariance (strong invariance). The source of noninvariance of intercepts in the disengagement factor was investigated by working backwards and sequentially releasing item intercept constraints for individual indicators and retesting the model with the aim of arriving at a partially invariant model. This process suggested that the avoidance indicator appeared to be the primary source of noninvariance at the scalar level for the measurement model. A partially invariant model of the disengagement factor without intercept constraints for avoidance demonstrated scalar invariance (strong invariance). Although standards for partial invariance vary, this disengagement factor supporting invariance in 3 out of 4 indicators suggested adequate partial invariance to be used for examining mean differences on a latent factor in substantive analyses (Steenkamp & Baumgartner, 1998; Vandenburg & Lance, 2000). In summary, the SCE and DIS factors both demonstrated relatively strong degrees of measurement invariance. Thus, analyses for Aim 2 (testing unidirectional vs. transactional models of ER and caregiver adjustment) proceeded using the partially invariant disengagement latent factor and the invariant secondary coping latent factor.

Aim 2: Testing Uni-directional vs. Transactional Models of Relations Between ER and Caregiver Adjustment Outcomes Over Time.

Nested model comparisons were used to test the hypothesis that a bidirectional rather than a unidirectional relationship exists between caregiver ER and adjustment outcomes of psychopathology, health, and treatment related stress during the first year of treatment. A visual depiction of each hypothesized model structure that was tested is presented in Figure 3 for SCE and depression, and Figure 4 for DIS and depression as examples. Results with model fit information and a series of chi-square difference tests for nested models for each ER factor with each adjustment outcome are presented in Tables 4-13.

Secondary Control Engagement (SCE) Factor Models

Secondary control engagement & depression. Based on fit indices, none of the SCE and depression models demonstrated adequate fit (see Table 4). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Figure 2: Model D), and the depression predicting SCE model (Figure 2: Model B) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Figure 2: Model A), and the SCE predicting depression model (Figure 2: Model C), but not significantly better fit compared to the depression predicting SCE model (Figure 2: Model B).

Secondary control engagement & anxiety. Fit indices suggested that none of the SCE and anxiety models demonstrated adequate fit (see Table 5). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D), and the anxiety predicting SCE model (Model B) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), and the SCE predicting anxiety model (Model C), but not significantly better fit compared to the anxiety predicting SCE model (Model B).

Secondary control engagement & PTSS. Based on fit indices, none of the SCE and PTSS models demonstrated adequate fit (see Table 6). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D), and the PTSS predicting SCE model (Model B) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), and the SCE predicting PTSS model (Model C), but not significantly better fit compared to the PTSS predicting SCE model (Model B).

Secondary control engagement & treatment related stress. Fit indices suggested that none of the SCE and treatment related stress models demonstrated adequate fit (see Table 7). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D), and the treatment related stress predicting SCE model (Model B) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), and the SCE predicting treatment related stress model (Model C), but not significantly better fit compared to the treatment related stress predicting SCE model (Model B).

Secondary control engagement & health. Based on fit indices, none of the SCE and health models demonstrated adequate fit (see Table 8). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D), and the health predicting SCE model (Model B) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), and the SCE predicting health model (Model C), but not significantly better fit compared to the health predicting SCE model (Model B).

Disengagement (DIS) Factor Models

Disengagement & depression. Fit indices suggested that none of the DIS and depression models demonstrated adequate fit (see Table 9). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Figure 3: Model D) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Figure 3: Model A), the DIS predicting depression model (Figure 3: Model C), and the depression predicting DIS model (Figure 3: Model B).

Disengagement & anxiety. Based on fit indices, none of the DIS and anxiety models demonstrated adequate fit (see Table 10). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D), and the DIS predicting anxiety model (Model C) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), and the anxiety predicting SCE model (Model B), but not significantly better fit compared to the DIS predicting anxiety model (Model C).

Disengagement & PTSS. Based on comparisons of fit indices, none of the DIS and PTSS models demonstrated adequate fit (see Table 11). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), the DIS predicting PTSS model (Model C), and the PTSS predicting DIS model (Model B).

Disengagement & treatment related stress. Based on fit indices, none of the DIS and treatment stress models demonstrated adequate fit (see Table 12). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), the DIS predicting treatment stress model (Model C), and the treatment stress predicting DIS model (Model B).

Disengagement & health. Comparisons of fit indices suggested that none of the DIS and health models demonstrated adequate fit (see Table 13). The transactional model in which all autoregressive and reciprocal paths in both directions were included (Model D) showed the best relative fit of the models tested. Chi-square difference tests suggested that the transactional model had better fit compared to the baseline model (Model A), the DIS predicting health model (Model C), and the health predicting DIS model (Model B).

Post-hoc model re-specifications for Aim 2

Given that none of the originally hypothesized models for aim 2 demonstrated adequate fit, post-hoc data driven re-specifications were conducted in an effort to improve model fit. The starting models for re-specifications were the transactional models, given that the transactional models overall showed the best fit in model comparisons (see above), and these models contained regression paths that would address substantive research questions posed by the current study (the influence of ER factors on adjustment and vice versa). The post-hoc model re-specification process and rationale is described below for the SCE and depression model. A similar process was followed for all of the originally hypothesized models in Aim 2, for which the process is also described below.

Re-specifications for SCE & depression. First, additional auto-regressive paths were added for both the SCE factor and depression, estimating the relation of observations at time 1 on observations at time 3. These paths were added to assess whether time 1 observations explained additional variance at time 3, that was not already explained by the autoregressive influence from time 2. In addition, correlations between SCE and depression at time 2, as well as correlations between SCE and depression at time 3 were added, to test whether concurrent associations between SCE and depression helped explain variance in each factor that was not already being explained via cross-lagged paths. With these new paths added to the model, fit indices suggested that the model still did not demonstrate adequate fit (RMSEA = .11, SRMR = .10, CFI = .75, TLI = .72, AIC/BIC = 7167.41/7288.88, $\chi^2(94) = 248.09$, $p < .001$).

Next, latent factors were added to estimate common method variance for all indicators in the SCE factor (cognitive restructuring, acceptance, positive thinking, and distraction). Common method variance is systematic error variance accounted for by the measurement method, rather than true variance related to the construct itself (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Richardson, Simmering, & Sturman, 2009). Common method bias can deflate or inflate intercorrelations between variables in a statistical model (Williams & Brown, 1994). Thus, specifying and estimating latent common method variance factors for ER indicators was done in an attempt to decrease potential noise/error in the estimates due to method bias, and to improve overall model fit. The model with a common method factor for each indicator resulted in estimates of negative variance, suggesting an estimation problem. The examined output of the model indicated that the source of the negative variance estimate was in relation to the positive thinking indicator at time 1, thus the model was re-specified to exclude a common method factor for positive thinking. This next model was successfully estimated with no negative variances, and showed adequate fit (RMSEA = .05, SRMR = .08, CFI = .96, TLI = .95, AIC/BIC = 7048.93/7205.96, χ^2 (82) = 105.61, *p* = .04). All of the ER indicators in this model showed significant loadings for the SCE factors at all time points, as well as on the method variance factor estimates, thus this portion of the model was retained given its contribution to significant improvements in model fit. Autoregressive paths between time 1 SCE and time 3 SCE (*B* = -.18, *SE* = .21, *p* = .41), and between time 1 depression and time 3 depression (*B* = .06, *SE* = .10, *p* = .52) were non-significant, and thus were trimmed. Similarly, relations between SCE and depression at time 2 (*B* = -.00, *SE* = .49, *p* = .99) and at time 3 (*B* = .11, *SE* = .34, *p* = .74) were non-significant and were also trimmed. Fit indices for this final model, which built on the originally tested bi-directional model by including estimates of common method variance for 3 ER indicators (cognitive restructuring, acceptance, distraction; see Figure 5) demonstrated good fit to the data (RMSEA = .04, SRMR = .08, CFI = .96, TLI = .96, AIC/BIC = 7041.73/7178.02, χ^2 (89) = 112.51, *p* = .05).

Re-specifications for SCE & anxiety model. Auto-regressive paths were added for both the SCE factor and anxiety, estimating the relation of observations at time 1 on observations at time 3. In addition, correlations between SCE and anxiety at time 2, as well as correlations between SCE and anxiety at time 3 were added. This model resulted in negative variance estimates for the SCE factor at time 3 suggesting an estimation problem, thus autocorrelations between time 1 and 3 SCE and time 1 and 3 anxiety were trimmed, as were correlations between SCE and anxiety at time 2 and 3. Next, latent factors were added to estimate common method variance for all indicators in the SCE factor (cognitive restructuring, acceptance, positive thinking, and distraction). This model with a common method factor for each indicator resulted in an error that suggested the model did not converge. The model output indicated that, similar to the SCE and depression model with common method factors (see above), the SCE and anxiety model resulted in a negative variance estimate for the positive thinking indicator. Thus, the model was re-specified to exclude a common method factor for positive thinking. This final model (see Figure 6) was estimated with no negative variances, and showed adequate fit (RMSEA = .05, SRMR = .10, CFI = .95, TLI = .94, AIC/BIC = 6710.90/6847.19, $\chi^2(89) = 119.85$, $p = .02$). All of the indicators in this final model showed significant loadings for the SCE factors at all time points, as well as on the method variance factor estimates.

Re-specifications for SCE & PTSS model. Auto-regressive paths were added for both the SCE factor and PTSS, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between SCE and PTSS at time 2, as well as correlations between SCE and PTSS at time 3 were added. Fit indices suggested that this model still did not demonstrate adequate fit (RMSEA = .12, SRMR = .12, CFI = .71, TLI = .68, AIC/BIC = 7765.07/7886.54, $\chi^2(94) = 284.90$, $p < .001$).

Next, latent factors were added to estimate common method variance for all indicators in the SCE factor (cognitive restructuring, acceptance, positive thinking, and distraction). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge. Although the model output did not indicate negative variance estimates for the positive thinking indicator, given that this was a source of model misfit in the previous SCE models (see above), the model was re-specified to exclude a common method factor for positive thinking. This next model was successfully estimated and showed improved fit (RMSEA = .07, SRMR = .11, CFI = .91, TLI = .88, AIC/BIC = 7648.62/7805.65, $\chi^2(82)$ = 144.45, $p < .001$). All of the indicators in this model showed significant factor loadings for the SCE factor at all time points, as well as on the method variance factor estimates, thus this portion of the model was retained given its contribution to improvements in model fit. Autoregressive paths between time 1 SCE and time 3 SCE (*B* = -.09, *SE* = .19, *p* = .62), and between time 1 depression and time 3 PTSS (*B* = .11, *SE* = .10, *p* = .28) were non-significant, and thus were trimmed. Similarly, relations between SCE and PTSS at time 2 (*B* = .51, *SE* = 1.01, *p* = .61) and at time 3 (*B* = 1.02, *SE* = 1.13, *p* = .37) were non-significant and were also trimmed. The final model for SCE and PTSS (see Figure 7) built on the originally tested bi-directional model by including estimates of common method variance for 3 ER indicators (cognitive restructuring, acceptance, distraction), and still fell short of demonstrating adequate fit to the data (RMSEA = .07, SRMR = .11, CFI = .91, TLI = .89, AIC/BIC = 7640.65/7776.94, $\chi^2(89)$ = 150.48, $p <$ .001).

Re-specifications for SCE & treatment related stress model. Auto-regressive paths were added for both the SCE factor and treatment related stress, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between SCE and treatment related stress at time 2, as well as correlations between SCE and treatment related stress at time 3 were added. Fit indices suggested that this model still did not demonstrate adequate fit (RMSEA = .12, SRMR = .11, CFI = .69, TLI = .65, AIC/BIC = 7688.46/7809.93, χ^2(94) = 284.08, p < .001).

Next, latent factors were added to estimate common method variance for all indicators comprising the SCE factor (cognitive restructuring, acceptance, positive thinking, and distraction). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge. Given that the method variance factor for the positive thinking indicator was a source of model misfit in the previous SCE models (see above), the model was re-specified to exclude a common method factor for positive thinking. This next model was successfully estimated and showed improved fit (RMSEA = .07, SRMR = .09, CFI = .90, TLI = .87, AIC/BIC = 7572.91/7729.94, χ^2(82) = 144.53, p < .001). All of the SCE indicators in this model showed significant loadings for the SCE factors at all time points, as well as on the method variance factor estimates, thus this portion of the model was retained given it's contribution to improvements in model fit. Autoregressive paths between time 1 SCE and time 3 SCE (B = -.06, SE = .20, p = .77), and between time 1 treatment related stress and time 3 treatment related stress (B = .02, SE = .12, p = .84) were non-significant, and thus were trimmed. Similarly, correlations between SCE and treatment related stress at time 2 (B = 1.29, SE = 1.61, p = .42) and at time 3 (B = 1.17, SE = 1.51, p = .44) were non-significant and were also trimmed. This final model (see Figure 8) which built on the originally tested bi-directional model by including estimates of common method variance for 3 ER indicators (cognitive restructuring, acceptance, distraction), still fell short of demonstrating adequate fit to the data (RMSEA = .07, SRMR = .09, CFI = .90, TLI = .88, AIC/BIC = 7563.03/7699.32, χ^2(89) = 148.65, p < .001).

Re-specifications for SCE & health model. Auto-regressive paths were added for both the SCE factor and health, estimating the relation of observations at time 1 on observations at time 3. In addition, correlations between SCE and health at time 2, as well as correlations between SCE and health at time 3 were added. This model resulted in negative variance estimates for the SCE factor at time 3, suggesting an estimation problem, thus autocorrelations between time 1 and 3 SCE and time 1 and 3 health were removed, as were correlations between SCE and health at time 2 and 3. Next, latent factors were added to estimate common method variance for all indicators in the SCE factor (cognitive restructuring, acceptance, positive thinking, and distraction). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge. Given that the method variance factor for the positive thinking indicator was a source of model misfit in the previous SCE models (see above), the model was re-specified to exclude a common method factor for positive thinking. This final model (see Figure 9) was estimated with no negative variances, and showed adequate fit to the data (RMSEA = .05, SRMR = .08, CFI = .95, TLI = .94, AIC/BIC = 5623.29/5759.58, $\chi^2(89)$ = 123.00, p = .01). All of the SCE indicators in this model showed significant loadings for the SCE factor at all time points, as well as on the method variance factor estimates.

Re-specifications for DIS & depression model. Auto-regressive paths were added for both the DIS factor and depression, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between SCE and depression at time 2, as well as correlations between SCE and depression at time 3 were added. Fit indices suggested that this model still did not demonstrate adequate fit (RMSEA = .11, SRMR = .11, CFI = .80, TLI = .77, AIC/BIC = 7111.39/7238.79, $\chi^2(92)$ = 253.49, p < .001). Autoregressive paths between time 1 DIS and time 3 DIS (B = -.41, SE = .29, p = .15), and between time 1 depression and time 3 depression (B = .05, SE = .10, p = .60) were non-significant, and thus were trimmed. Relations between DIS and depression at time 2 (B = 3.64, SE = 1.02, p < .001) and time 3 (B = 1.07, SE = .57, p = .06) showed relatively strong associations and were thus retained in the model.

Next, latent factors were added to estimate common method variance for all indicators in the DIS factor (wishful thinking, acceptance, denial, and avoidance). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge, and available output indicated a large negative variance estimate for the avoidance indicator at time 2. Thus, the model was re-specified to exclude a common method factor for avoidance. This next model was successfully estimated and showed substantially improved fit (RMSEA = .06, SRMR = .08, CFI = .95, TLI = .93, AIC/BIC = 7004.23/7161.26, χ^2(82) = 126.34, p = .002). All of the indicators in this model showed significant loadings for the DIS factor at all time points, with the exception of acceptance. In this model the factor loadings for the acceptance indicator suggested that acceptance was no longer a significant indicator for DIS (B = -.05, SE = .10, p = .64). Thus, the acceptance indicator (as well as the method variance factor for acceptance) was trimmed from the DIS measurement model. Trimming acceptance out of the measurement model of DIS further improved the fit to the data, and this final model (see Figure 10) showed acceptable fit according to fit indices (RMSEA = .05, SRMR = .06, CFI = .97, TLI = .96, AIC/BIC = 5623.68/5754.05, χ^2(46) = 64.33, p = .04). All of the DIS indicators in this model showed significant loadings for the DIS factors at all time points, as well as on the method variance factor estimates.

Re-specifications for DIS & anxiety model. Auto-regressive paths were added for both the DIS factor and anxiety, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between DIS and anxiety at time 2, as well as correlations between DIS and anxiety at time 3 were added. This model resulted in an error and negative variance estimate for the DIS factor at time 3, suggesting an estimation problem and possible misspecification around the DIS factor component of the model. The autoregressive path from DIS at time 1 to DIS at time 3 was trimmed, and the model was re-run. This model was successfully estimated with no negative variances, but still showed poor fit (RMSEA = .11, SRMR = .11, CFI = .78, TLI = .76, AIC/BIC = 6791.89/6916.33, $\chi^2(93) = 257.01$, $p < .001$). The autoregressive path between time 1 anxiety and time 3 anxiety (B = -.41, SE = .29, p = .15), and between time 1 anxiety and time 3 anxiety (*B* = .13, *SE* = .09, *p* = .12) was non-significant, as was the relation between time 3 DIS and time 3 anxiety (*B* = 0.20, *SE* = .37, *p* = .60), and thus these paths were trimmed. The correlation between DIS and anxiety at time 2 (*B* = 1.68, *SE* = .54, p = .003) was retained.

Next, latent factors were added to estimate common method variance for all indicators in the DIS factor (wishful thinking, acceptance, denial, and avoidance). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge. Given that the common method factor estimates for acceptance and avoidance were a significant source of misspecification in the DIS and depression model (see above), the model was re-specified to exclude these parameters. This next model was successfully estimated and showed improved but still relatively poor fit (RMSEA = .09, SRMR = .11, CFI = .86, TLI = .83, AIC/BIC = 6738.46/6880.67, $\chi^2(87) = 191.57$, $p < .001$). Given that the acceptance indicator, similar to the DIS and depression model (see above), was the weakest indicator of DIS, the next model tested was one which excluded acceptance from the DIS measurement model. The fit was further improved, and this final DIS and anxiety model (see Figure 11) showed acceptable fit

(RMSEA = .06, SRMR = .07, CFI = .97, TLI = .95, AIC/BIC = 5293.72/5418.16, χ^2 (48) = 70.73, p = .02).

Re-specifications for DIS & PTSS model. Auto-regressive paths were added for both the DIS factor and PTSS, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between DIS and PTSS at time 2, as well as correlations between DIS and PTSS at time 3 were added. Fit indices suggested that this model still showed poor fit to the data (RMSEA = .11, SRMR = .13, CFI = .81, TLI = .78, AIC/BIC = 7653.93/7775.41, χ^2 (94) = 263.93, p < .001).

Next, latent factors were added to estimate common method variance for all indicators in the DIS factor (wishful thinking, acceptance, denial, and avoidance). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge. Given that the common method factor estimate for avoidance was a significant source of misspecification in the DIS and depression and anxiety models (see above), the next model was re-specified to exclude this parameter. This next model was successfully estimated and showed improved fit (RMSEA = .06, SRMR = .08, CFI = .95, TLI = .94, AIC/BIC = 7539.65/7702.61, χ^2 (80) = 121.65, p = .004).

Autoregressive paths between time 1 DIS and time 3 DIS (*B* = -.06, *SE* = .19, p = .76), and between time 1 PTSS and time 3 PTSS (*B* = .09, *SE* = .09, p = .31) were non-significant, and thus were trimmed. Relations between DIS and PTSS at time 2 (*B* = 9.40, *SE* = 2.05, p < .001) and at time 3 (*B* = 4.79, *SE* = 1.81, p = .006) showed strong associations and were thus retained in the model. All of the indicators in this model showed significant loadings for the DIS factor at all time points, with the exception of acceptance. In this model the factor loadings for the acceptance indicator suggested that acceptance was no longer a significant indicator for DIS (*B* =

-.00, *SE* = .09, *p* = .98). Thus, the acceptance indicator (as well as the method variance factor for acceptance) was trimmed from the next model. The fit was further improved, and this final model (see Figure 12) showed acceptable fit (RMSEA = .06, SRMR = .06, CFI = .97, TLI = .96, AIC/BIC = 6159.54/6289.91, χ^2 (46) = 67.38, *p* = .02). All of the remaining DIS indicators in this model showed significant loadings for the DIS factors at all time points, as well as on the method variance factor estimates.

Re-specifications for DIS & treatment related stress model. Auto-regressive paths were added for both the DIS factor and treatment related stress, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between DIS and treatment related stress at time 2, as well as correlations between DIS and treatment related stress at time 3 were added. Fit indices suggested that this model still showed poor fit (RMSEA = .11, SRMR = .11, CFI = .77, TLI = .74, AIC/BIC = 7652.73/7780.14, χ^2 (92) = 258.15, *p* < .001).

Next, latent factors were added to estimate common method variance for all indicators in the DIS factor (wishful thinking, acceptance, denial, and avoidance). The model with a common method factor for each indicator resulted in an error that suggested the model did not converge. Given that the common method factor estimate for avoidance was a significant source of misspecification in the previous DIS models (see above), the next model was re-specified to exclude this parameter. This next model was successfully estimated and showed significantly improved fit (RMSEA = .05, SRMR = .08, CFI = .96, TLI = .95, AIC/BIC = 7525.94/7688.89, χ^2 (80) = 107.35, *p* = .02).

Autoregressive paths between time 1 DIS and time 3 DIS (*B* = .01, *SE* = .14, *p* = .92), and between time 1 treatment related stress and time 3 treatment related stress (*B* = .02, *SE* = .11, *p* =

.83) were non-significant, as was the relation between DIS and treatment related stress at time 3 (*B* = 2.06, *SE* = 2.78, *p* = .46), and thus were trimmed. The concurrent relation between DIS and treatment related stress at time 2 (*B* = 16.00, *SE* = 3.48, *p* < .001) was retained in the model. All of the indicators in this model showed significant loadings for the DIS factor at all time points, with the exception of acceptance. In this model the factor loadings for the acceptance indicator suggested that acceptance was no longer a useful indicator for DIS (*B* = .08, *SE* = .10, *p* = .40). Thus, the acceptance indicator (as well as the method variance factor for acceptance) was trimmed from the DIS measurement model. The fit was further improved, and this final model (see Figure 13) showed good fit to the data (RMSEA = .04, SRMR = .06, CFI = .98, TLI = .98, AIC/BIC = 6146.16/6273.57, $\chi^2(47) = 57.40$, *p* = .14). All of the indicators in this model showed significant loadings for the DIS factor at all time points, as well as on the method variance factor estimates.

Re-specifications for DIS & health model. Auto-regressive paths were added for both the DIS factor and health, estimating the relation of observations for each variable at time 1 on observations for each variable at time 3. In addition, correlations between DIS and health at time 2, as well as correlations between DIS and health at time 3 were added. Fit indices suggested that this model still showed poor fit (RMSEA = .11, SRMR = .11, CFI = .81, TLI = .78, AIC/BIC = 5718.23/5845.63, $\chi^2(92) = 239.12$, *p* < .001).

Next, latent factors were added to estimate common method variance for all indicators in the DIS factor (wishful thinking, acceptance, denial, and avoidance). This model was successfully estimated and showed substantially improved fit (RMSEA = .03, SRMR = .07, CFI = .99, TLI = .98, AIC/BIC = 5596.41/5771.22, $\chi^2(76) = 85.30$, *p* = .22). The autoregressive path between time 1 DIS and time 3 DIS (*B* = -.03, *SE* = .19, *p* = .86), as well as the relation between

DIS and health at time 3 (B = -.12, SE = .10, p = .21) were non-significant, and thus were trimmed. The autoregressive path between time 1 health and time 3 health (*B* = .30, *SE* = .11, *p* = .010) and the relation between DIS and health at time 2 (*B* = -.39, *SE* = .09, *p* < .001) were retained. In this model the factor loadings for the acceptance indicator suggested that acceptance was no longer a significant indicator of DIS (*B* = .12, *SE* = .10, *p* = .26). Thus, the acceptance indicator (as well as the method variance factor for acceptance) was trimmed from the DIS measurement model. The fit was further improved, and this final model (see Figure 14) showed good fit to the data (RMSEA = .01, SRMR = .05, CFI = .99, TLI = .99, AIC/BIC = 4225.00/4361.29, χ^2 (44) = 45.03, *p* = .43). All of the indicators in this model showed significant loadings for the DIS factors at all time points, as well as on the method variance factor estimates.

Temporal patterns between ER & Adjustment

Path coefficients from the final best fitting models were interpreted to determine specific temporal patterns of influence between ER and adjustment factors over time. Figures 5 – 14 show the final models with standardized path estimates for each ER factor with each adjustment outcome. A summary of temporal patterns and direction of effects between ER and adjustment variables are described in Table 14.

SCE & depression. All autoregressive paths for both the SCE factor and depression were strong, as expected, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 5). Cross lagged path estimates indicated that depression at time 1 predicted SCE at time 2 (*ß* = -.12, *p* < .001), and depression at time 2 predicted SCE at time 3 (*ß* = -.11, *p* < .001). Cross lagged paths between SCE at time 1 and depression at time 2 (*ß* = .10, *p* = .30), and SCE at time 2 and depression at time 3 (*ß* = .03, *p* = .73) were non-significant. Results supported a uni-directional relation between SCE and depression, with higher depression predicting lower levels of SCE at later time points over the first year of treatment.

SCE & anxiety. All autoregressive paths for both the SCE factor and anxiety were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 6). Cross lagged path estimates indicated that anxiety at time 1 significantly predicted SCE at time 2 ($ß = -.17$, $p = .008$). Anxiety at time 2 predicting SCE at time 3 fell short of significance ($ß = -.14$, $p = .09$), as did cross lagged paths between SCE at time 1 and anxiety at time 2 ($ß = -.03$, $p = .75$) and SCE at time 2 and anxiety at time 3 ($ß = .01$, $p = .89$). Overall, results supported a uni-directional relation between SCE and anxiety, with higher anxiety shortly after the diagnosis predicting lower levels of SCE at time 3 (6 months).

SCE & PTSS. All autoregressive paths for both the SCE factor and PTSS were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 7). Cross lagged path estimates indicated that PTSS at time 1 significantly predicted SCE at time 2 ($ß = -.12$, $p = .003$). PTSS at time 2 also significantly predicted SCE at time 3 ($ß = -.12$, $p = .027$). Cross lagged paths between SCE at time 1 and PTSS at time 2 ($ß = .10$, $p = .20$), and SCE at time 2 and PTSS at time 3 ($ß = -.01$, $p = .90$) were non-significant. Overall, results supported a uni-directional relation between SCE and PTSS, with higher anxiety predicting lower levels of SCE at later time points over the first year of treatment.

SCE & treatment related stress. All autoregressive paths for both the SCE factor and treatment related stress were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 8). Cross lagged path estimates indicated that treatment related stress at time 1 predicted SCE at time 2 ($ß = -.08$, $p < .001$), and treatment related stress at time 2 predicted SCE at time 3 ($ß = -.09$, $p = .007$). Cross lagged paths between SCE at time 1 and treatment related stress at time 2 ($ß = -.04$, $p = .67$), and SCE at time 2 and treatment related stress at time 3 ($ß = .01$, $p = .92$) were non-significant. Results supported a uni-directional relation between SCE and treatment related stress, with higher treatment related stress predicting lower levels of SCE at later time points over the first year of treatment.

SCE & health. All autoregressive paths for both the SCE factor and health were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 9). Cross lagged path estimates indicated that health at time 1 predicted SCE at time 2 ($ß = -.06$, $p < .001$), and health at time 2 predicted SCE at time 3 ($ß = -.06$, $p = .003$). Cross lagged paths between SCE at time 1 and health at time 2 ($ß = -.13$, $p = .11$), and SCE at time 2 and health at time 3 ($ß = .03$, $p = .77$) were non-significant. Results supported a surprising uni-directional pattern of relations between SCE and health, with better health predicting lower levels of SCE at later time points over the first year of treatment.

DIS & depression. All autoregressive paths for both the DIS factor and depression were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 10). Cross lagged path estimates indicated that depression at time 1 significantly predicted DIS at time 2 ($ß = -.06$, $p = .03$). Depression at time 2 did not predict DIS at time 3 ($ß = -.04$, $p = .27$). The cross lagged path between DIS at time 1 and depression at time 2 ($ß = .29$, $p = .01$) was significant, though DIS at time 2 and depression at time 3 did not show a significant relation ($ß = .12$, $p = .23$). Results supported an unexpected transactional relation between DIS and depression during the first 6 months following diagnosis, with higher depression around the time of diagnosis predicting *lower* levels of DIS at 6 months, and higher DIS around the time of diagnosis predicting *higher* depression at 6 months.

DIS & anxiety. All autoregressive paths for both the DIS factor and anxiety were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 11). Cross lagged path estimates indicated that anxiety at time 1 was not significantly predictive of DIS at time 2 (*ß* = -.05, *p* = .37), and neither was anxiety at time 2 predictive of DIS at time 3 (*ß* = -.04, *p* = .50). The cross lagged path between DIS at time 1 and anxiety at time 2 (*ß* = .37, *p* = .001) was significant, though DIS at time 2 and anxiety at time 3 fell short of demonstrating a significant relation (*ß* = .21, *p* = .07). Results supported a uni-directional relation between DIS and anxiety during the first 6 months following diagnosis, with higher DIS around the time of diagnosis predicting higher levels of anxiety at 6 months.

DIS & PTSS. All autoregressive paths for both the DIS factor and PTSS were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 12). Cross lagged path estimates indicated that higher PTSS at time 1 predicted lower DIS at time 2 (*ß* = -.08, *p* = .038). PTSS at time 2 did not predict DIS at time 3 (*ß* = -.05, *p* = .23). Cross lagged path estimates also showed that higher DIS at time 1 was associated with higher PTSS at time 2 (*ß* = .33, *p* = .001), though DIS at time 2 and PTSS at time 3 fell short of demonstrating a significant relation (*ß* = .24, *p* = .08). Again, results supported a an unexpected transactional relation between DIS and PTSS during the first 6 months following diagnosis, with higher PTSS around the time of diagnosis predicting *lower* levels of DIS at 6 months, and higher DIS around the time of diagnosis predicting *higher* PTSS at 6 months.

DIS & treatment related stress. All autoregressive paths for both the DIS factor and treatment related stress were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 13). Cross lagged path estimates indicated that higher treatment related stress at time 1 predicted lower DIS at time 2 (*ß* = -.06, p = .004). Higher treatment related stress at time 2 also predicted lower DIS at time 3 (*ß* = -.06, p = .025). The cross lagged path between DIS at time 1 and treatment related stress at time 2 (*ß* = .11, p = .34), and DIS at time 2 and treatment related stress at time 3 (*ß* = .18, p = .09) did not show a significant relation. Results supported an unexpected uni-directional relation between DIS and treatment related stress, with higher treatment related stress predicting lower levels of DIS at later time points over the first year of treatment.

DIS & health. All autoregressive paths for both the DIS factor and caregiver health were strong, suggesting that previous levels of each construct were good predictors of future observations of the same construct (see Figure 14). Cross lagged path estimates indicated that better health at time 1 predicted lower DIS at time 2 (*ß* = -.04, p = .001). Better health at time 2 also predicted lower DIS at time 3 (*ß* = -.04, p = .007). The cross lagged path between DIS at time 1 and health at time 2 (*ß* = -.12, p = .19), and DIS at time 2 and health at time 3 (*ß* = -.10, p = .34) did not show a significant relation. Results supported a uni-directional relation between DIS and health, with better overall health predicting lower levels of DIS at later time points over the first year of treatment.

Aim 3: Testing the temporal precedence and dynamics of change between ER and adjustment outcomes.

Estimating latent change score (LCS) models for Aim 3 using each ER scale (SCE and DIS) with each adjustment scale proceeded as follows.

Univariate LCS Models

Seven univariate LCS models were fit to the data separately for measures of SCE, DIS, and adjustment outcomes of depression, anxiety, PTSS, treatment related stress, and health. Given that LCS models estimate latent change parameters based on observed variables (rather than latent variables), sum score versions of DIS and SCE factors were used for these models. The univariate models tested for each variable were: a) a proportional change model, where changes at each measurement interval are proportional to the level at the previous observation, b) a constant change model estimating a constant amount of change between each observation, c) a dual change model that included both constant change between each observation as well as change that was proportional to the level at the previous observation, and d) a changes-to-changes model with change represented as an estimate of constant change, change proportional to the level at the previous observation, and also change proportional to the previous *change* estimate. Fit indices for the univariate LCS models are presented in Tables 14-20.

Univariate latent change score models for SCE. According to fit indices for the univariate latent change score models for SCE, the proportional change model showed adequate fit (see Table 15). Fit statistics for the constant change and dual change model fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in reliably estimating the models. Fit statistics for the Changes-to-Changes model were not available due to model non-convergence.

Univariate latent change score models for DIS. According to fit indices for the univariate latent change score models for DIS, the proportional change model showed adequate fit, as did the constant change model (see Table 16). Fit statistics for the dual change model fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in reliably estimating the model. Fit statistics for the Changes-to-Changes model were not available due to model non-convergence.

Univariate latent change score models for depression. According to fit indices for the univariate latent change score models for depression, the proportional change model showed poor fit, as did the constant change model (see Table 17). Fit statistics for the dual change model and the Changes-to-changes model fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in model estimation.

Univariate latent change score models for anxiety. For the univariate latent change score models for anxiety (see Table 18), fit statistics for the proportional change, constant change, dual change and the Changes-to-changes models all fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in reliably estimating the models.

Univariate latent change score models for PTSS. According to fit indices for the univariate latent change score models for PTSS, the proportional change model showed good fit (see Table 19). Fit statistics for the constant change model, dual change model, and the Changes-to-changes model fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in model estimation.

Univariate latent change score models for treatment related stress. According to fit indices for the univariate latent change score models for treatment related stress, the proportional change model showed poor fit, as did the constant change model (see Table 20). Fit statistics for the dual change model and the Changes-to-changes model fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in model estimation.

Univariate latent change score models for health. For the univariate latent change score models for health (see Table 21), fit statistics for the proportional change, constant change, dual change and the Changes-to-changes models all fell outside of the range of expected values, and thus were not interpretable, suggesting difficulties in reliably estimating the models.

Univariate latent change score models summary. Overall, the univariate latent change structure was a poor fit to the data across ER factors (DIS and SCE) as well as caregiver adjustment outcomes.

Bivariate Latent Change Models

Although univariate LCS models resulted in estimation problems suggesting lack of power and/or poor fit to the data (see above), bivariate LCS models were still tested as originally proposed. Ten separate bivariate LCS models were specified for DIS and SCE factors with each adjustment variable (depression, anxiety, PTSS, treatment related stress, and health). All bivariate LCS models were tested both with and without estimating coupling parameters between variables. Each of the bivariate LCS models resulted in errors, negative variance estimates for latent and observed variables, and problems with model convergence.

CHAPTER 4 | Discussion

Discussion

Models of psychopathology have increasingly incorporated emotion regulation (ER) as a core process underlying the etiology and treatment of mental health problems (Campbell-Sills & Barlow, 2007; Kring & Sloan, 2010; Sheppes, Suri, & Gross, 2015). Despite the strong evidence supporting ER as a correlate of a wide range of psychopathology, there has been surprisingly few studies examining the temporal associations between ER and psychological adjustment outcomes. This gap in the scientific literature of ER makes it unclear whether ER functions as a risk factor, a contemporaneous correlate, or a consequence of maladjustment. Questions about temporal relations between ER and adjustment outcomes are particularly needed in at risk samples such as pediatric cancer. Advancements in treatment have led to increased survival rates for children diagnosed with cancer, and research in this area has subsequently shifted its aims to understanding psychosocial adjustment of survivors and their families (Patenaude & Kupst, 2004). Many caregivers of children with cancer experience ongoing stress well beyond the initial shock of the diagnosis, including an increased need for regulating a variety of difficult emotions as their child's treatment progresses (Kazak et al., 2005; Sloper, 2000; Van Dongen-Melman et al., 1998; Wijnberg-Williams, Kamps, Klop, & Hoekstra-Weebers, 2005). Although many caregivers' psychological distress decreases to normative levels over time, a subset remain clinically distressed (Katz et al., 2018). Given such variability in caregiver outcomes, it is important to identify risk and protective factors that help explain which caregivers adapt well following the stress of their child's illness. Thus, the current study aimed to examine temporal associations between ER and a range of adjustment outcomes including psychopathology (depression, anxiety, and PTSS), treatment related stress, and physical health in caregivers of children with cancer.

Aim 1: Measurement of ER in Caregivers of Children with Cancer

The first aim of the current study was to test a measurement model of ER. Despite the ever growing literature on ER, one of the most prevalent challenges of this research continues to be the use of valid and reliable measures (Berking & Wupperman, 2012; Bridges, Denham, & Ganiban, 2013). Clearly defining and testing a measurement model of ER is a useful first step before proceeding to examining substantive questions about ER and its relations with adjustment factors.

We drew on previous theoretical and empirical literature to conceptualize a measurement model of ER. Earlier work suggests that ER can be predominantly broken down into positive (or adaptive) and negative (or maladaptive) strategies (Aldao et al., 2010; Aldao, Jazaieri, Goldin, & Gross, 2014; John & Gross, 2004). The most frequently studied positive strategies, which include cognitive reappraisal, acceptance, and problem solving, have been positively correlated with improved psychological functioning. Negative or maladaptive strategies such as rumination, expressive suppression, and avoidance have been positively correlated with negative outcomes (Aldao et al., 2010). Despite ER being consistently conceptualized into positive vs. negative domains, some authors have cast doubt over the idea that ER strategies can be so consistently differentiated (Kashdan, Young, & Machell, 2015). Thus, the current study aimed to utilize standardized measures of as many of the most commonly studied ER strategies as available in the current study sample, and to test whether these strategies would cluster into two ER factors (a negative and a positive) or a broader single ER factor.

The measurement method we utilized was caregiver self-report. Specifically, we used the Response to Stress Questionnaire (RSQ; Connor-Smith et al., 2000), which is a well validated measure of coping, and includes subscales measuring 5 of the 6 most commonly studied ER strategies (cognitive restructuring, problem solving, acceptance, rumination, and avoidance). Coping is a closely related construct which is conceptually indistinguishable from ER in many circumstances (Compas et al., 2017; Compas et al., 2014). Moreover, the RSQ has been used as a measure to assess ER in previous investigations (Feldman et al., 2006; Khor, Melvin, Reid, & Gray, 2014; Mazefsky, Borue, Day, & Minshew, 2014; Weiss, Thompson, & Chan, 2014). Using ER subscales from the RSQ, we originally proposed to test and compare two models of measurement for ER using confirmatory factor analysis (CFA): 1) a two factor model of ER representing positive (cognitive restructuring, acceptance, problem solving) and negative (rumination, avoidance) dimensions and 2) a one factor model which included both positive and negative strategies in a single factor.

Results of the CFA suggested that neither of these models adequately fit the data. Post-hoc analyses conducted to examine points of misspecification showed that the originally selected ER subscales exhibited some unexpected relations. In particular, problem solving appeared to be unrelated to any of the other adaptive strategies, and was positively related with rumination. These results are surprising, given that problem solving is an important regulatory strategy often taught and relied upon in cognitive behavioral therapy (CBT) (Beck et al., 1979; D'Zurilla, 1988; Marlatt et al., 1988). This finding might reflect the idea that problem solving has been found to be comprised of various sub processes, some of which includes worry and ruminative thinking (Borkovec & Roemer, 1995; Aldao & Nolen-Hoeksema, 2013). There has also been an increased emphasis on the importance of context when studying ER (Aldao, 2013; Bonnano & Burton, 2013; Aldao & Tull, 2015), and strategies that may be useful in one context may be ineffective, or even harmful in another context. Given that much of the emotion related to a child having cancer may have to do with factors outside of a caregivers' control (e.g., the medical treatment process, course of the child's illness and symptoms), there may be less utility for problem solving as a way to manage emotions in this context. Indeed, Greening & Stoppelbein (2007) found that more use of problem solving was associated with higher rates of psychopathology symptoms in parents of children with cancer. Other research has found that problem solving interventions for caregivers of cancer patients have little to no effects on caregivers' emotional wellbeing (Blanchard, Toseland, & McCallion, 1996; Sherwood et al., 2012; Toseland, Blanchard, & McCallion, 1995). Moreover, Aldao & Nolen-Hoeksema (2012) found that problem solving is one of the strategies that appears to be implemented with more variability across contexts relative to other ER strategies, and the extent of implementation of problem solving is associated with higher rates of psychopathology. Thus, it may be that problem solving is a less functionally adaptive ER strategy for caregivers of children with cancer, and this is why it failed to show positive relations with other adaptive ER indicators and was correlated with rumination. Further work is needed to more clearly delineate problem solving as it pertains to ER, and empirically test under which conditions it functions as a useful strategy for managing emotion in this population.

After excluding problem solving in the ER models, the two factor and one factor models still failed to demonstrate adequate fit to the data. This led us away from our originally hypothesized measurement structure, as we proceeded to follow an exploratory process aimed at re-considering how different ER strategies may be conceptually organized. As a contrast to the conceptual distinction of purely adaptive vs. maladaptive strategies of ER, Compas et al. (2017) suggests that both ER and coping variables can be grouped into more specifically defined empirically and conceptually derived factors. These factors include problem-focused strategies, emotion-focused strategies, engagement/approach strategies, disengagement strategies, primary control strategies, secondary control strategies, and social support strategies. The strongest evidence of a theory driven model of separate factors for the RSQ that has been tested within a CFA framework comes from a handful of prior studies utilizing the RSQ across several samples (Benson et al., 2011; Compas et al., 2006; Connor-Smith & Calvete, 2004; Connor-Smith et al., 2000; Wadsworth, Rieckmann, Benson, & Compas, 2004; Xiao et al., 2010). This work has validated and replicated a three factor structure which includes a primary control factor (problem solving, emotional expression, emotional modulation), secondary control factor (i.e., acceptance, cognitive reappraisal, positive thinking, distraction), and a disengagement factor (i.e., avoidance, denial, wishful thinking). Given that a majority (three of the original five) of the ER subscales selected for the original measurement model fell into the secondary control coping and disengagement coping factors, these broader factors pulled from the coping literature were a starting point for testing a post-hoc re-vised model. Additional subscales were added for the secondary control coping (SCE) factor (distraction, positive thinking) and the disengagement coping (denial and wishful thinking) factors to build this two factor model.

Results showed that this new two factor model, based on factors derived from the coping literature, was an appropriate fit to the data. The conceptual structure most supported by the work of Aim 1 suggested that the SCE factor represented strategies characterized by changing how one thinks about stress and emotion, and the DIS factor represented strategies characterized by efforts to avoid or disengage from painful emotions and experiences. The acceptance subscale loaded on both factors in the measurement model of Aim 1, suggesting that it was making substantial and independent contributions to both the DIS and SCE factors. The direction of the loadings for acceptance suggested that the function of acceptance did not shift across factors, and that it was positively associated with the overall positive dimension of SCE, and negatively associated with the negative factor of DIS. These findings regarding the cross-loading suggest that some parts of acceptance are those related with other positive strategies such as cognitive restructuring and positive thinking, while other parts of acceptance are associated with lower levels of maladaptive responses. In both factors, it’s relation with other strategies suggested that acceptance was a uniformly adaptive strategy that could appear in both the presence of other positive strategies as well as in the absence of negative strategies. The prominence of acceptance in the measurement model is in line with the importance of this construct in acceptance based treatments, which suggest that individuals' abilities to accept their emotions and painful life circumstances significantly promotes their well-being (Eifert & Forsyth, 2005; Hayes et al., 1999). On the other hand, the DIS models in Aim 2 discussed below significantly improved once acceptance was dropped from the DIS factor, suggesting that when DIS is used as a predictor/outcome in relation to the current set of variables, acceptance does not load well onto DIS.

Results from Aim 1 have several implications for the study of ER and the closely related construct of coping, particularly in regard to measurement. Conclusions about the structure of measurement of ER from the current study can only be drawn in respect to the RSQ. In this regard, the measurement structure of the subscales of the RSQ in the current study sample match prior research using this measure (Benson et al., 2011; Compas et al., 2006; Connor-Smith & Calvete, 2004; Connor-Smith et al., 2000; Wadsworth, Rieckmann, Benson, & Compas, 2004; Xiao et al., 2010). Our results provide further evidence that secondary control strategies and disengagement strategies represent a conceptually and empirically distinct and valid group of ER/coping behaviors. Although the originally proposed two factor model (adaptive and maladaptive ER factors) did not fit well, post-hoc re-specifications of the measurement model still arrived at one expanded factor representing adaptive strategies (secondary control engagement), and another expanded factor representing maladaptive strategies (disengagement). This is consistent with the recent meta-analytic work of Naragon-Gainey et al., (2017), which similarly found that a single ER factor, as well as a broad adaptive-maladaptive two factor ER model does not fit a wide range of ER data. These authors also ultimately turned to exploratory analyses to reach a three factor model which included a disengagement factor (containing strategies such as avoidance) and an adaptive engagement factor (containing strategies such as cognitive reappraisal and acceptance). Such findings suggest that ER/coping strategies still tend to cluster by positive vs. negative factors, but rather than there being a single global adaptive and maladaptive factor, there may be multiple factors of various types of both adaptive and maladaptive factors. For instance, a third adaptive factor described in the coping literature is one comprised of primary control engagement (PCE) strategies, including ER constructs of emotional expression and problem solving (Wadsworth, Rieckmann, Benson, & Compas, 2004). Although problem solving did not fit with the ER measurement model as defined in the current study, a future direction of the current work should expand ER measurement models to include a PCE factor when assessing relations between caregiver ER and adjustment over time. Although the first aim of the current study ultimately had to rely on a data driven approach to establishing an adequate measurement model, this process ultimately contributed to much needed efforts at synthesizing theory and research on coping and ER (Compas et al., 2017). Specifically, this measurement work tested and compared theoretical models, drawn from both the ER and coping literature, regarding how specific ER/coping strategies are associated with one another. Although there is considerable overlap between ER and coping strategies, the current work suggests that the higher order dimensions or factors under which individual strategies fall under are not interchangeable between these two constructs. The current data did not support the conceptualization of global positive and negative ER dimensions, as commonly discussed in the ER literature. On the other hand, conceptualizing strategies into more well defined dimensions such as secondary control engagement and disengagement, as derived from the coping literature, appears to be an effective way of defining individual strategies. Such findings may have been largely due to the use of a measure specifically designed as a coping measure in the first place. Despite this, these results also suggest that the coping literature has great potential to inform how

ER strategies are conceptualized and measured. Future research employing gold standard measures of ER alongside measures like the RSQ can further increase our understanding of how similarly these constructs function with respect to psychological adjustment.

Aim 2: Transactional vs. Uni-directional Patterns of Relations Between ER, Psychopathology, Treatment Related Stress, & Health

The second aim of the current study compared uni-directional to transactional patterns in the relations between ER (SCE and DIS) and adjustment variables. Aim 2 was tested using a cross-lagged SEM panel design with three waves of measurement through the first year of treatment. Overall, the initial set of nested model comparisons showed that transactional relations between ER factors and adjustment variables were the best fit to the data. Despite this, none of these models showed acceptable fit, which precluded the ability to examine and interpret the direction and magnitude of the paths specified in even the relatively best fitting models. Thus, as with Aim 1, we pursued an exploratory data driven post-hoc process in an effort to uncover points of model misspecification to improve model fit. In most cases, adequate model fit was achieved by adding 1) contemporaneous correlations between the two variables of interest at time 1 (and sometimes also at times 2 and 3), and 2) estimating latent common method variance factors for ER.

There are several implications of these model re-specifications. First, the inclusion of contemporaneous correlations suggests that modeling how ER factors are related to adjustment outcomes when measured at the same timepoint is important when specifying longitudinal models between these variables. These contemporaneous correlation paths are conceptually obvious, and are in line with the wealth of correlational research showing that ER is associated with a wide range of adjustment outcomes (Berking & Wupperman, 2012). Second, the significant improvement in models achieved after modeling latent method variance factors suggests that systematic error in the previous models likely came from the fact that ER indices assessed at different time points shared covariance due to commonalities in the measurement method. Measurement context effects, consistency motif effects, and common rater effects are just a few specific potential sources of common method biases operating in the current ER data (see Podsakoff et al., 2003). Thus, using SEM to partial the substantive variance from the common method variance in this case helped improve model fit, and likely lead to more accurate path estimates. Although researchers vary widely in their views on common method variance, whether it exists, and what to do about it (Richardson, Simmering, & Sturman, 2009), the current findings suggest that future studies of ER/coping should strongly consider utilizing detection and correction techniques for common method variance.

Following the post-hoc re-specifications described above, paths from adequately fitting cross-lagged models were examined to assess substantive questions between the relations of caregiver ER and adjustment outcomes over the first year of their child's pediatric cancer treatment.

Temporal Relations Between ER and Adjustment Outcomes

The temporal relation between ER and psychopathology was one of the central questions of the current study. We aimed to gain insight into whether ER is a risk factor for, a correlate of, or consequence of symptoms of psychopathology, treatment related stress, and health. In our sample, bi-directional models of influence between ER and adjustment over the first year of treatment were an overall better fit to the data, supporting the notion that transactional patterns between these variables are more likely than uni-directional patterns. Despite this, examination of path estimates from adequately fitting models showed contrasting evidence. Path estimates showed stronger support for a uni-directional causal hypothesis of psychopathology, stress, and physical health predicting later levels of ER. The most consistent pattern emerged for the adaptive SCE strategies, suggesting that higher levels of anxiety, depression, PTSS, and treatment related stress prospectively predict lower levels of cognitive restructuring, acceptance, and distraction use. This pattern was seen across four out of five SCE models, with consistently small (ranging between -.08 to -.17) but significant standardized path estimates in each model across all timepoints. This suggests that overstressed caregivers of children with cancer who experience poor psychological adjustment are less likely to be able to draw on adaptive strategies to regulate their emotions as time goes on. In a more positive light, these findings suggest that a caregiver's ability to use healthy strategies for regulating emotion and coping with the stress of cancer can be bolstered by finding ways to manage treatment related stress and psychopathology symptoms. Interventions for this population, including psychoeducation and psychosocial based interventions (see Northouse et al., 2010; Kazak, 2005), which can alleviate caregiver distress and improve functioning are likely to have positive downstream effects in the form of strengthening caregivers' abilities to draw on adaptive ER strategies. Caregivers who utilize more adaptive ER strategies model healthier coping for the rest of the family, and are likely more present as caregivers, which ultimately fosters better child and family functioning.

Although the temporal pattern between caregiver physical health and SCE was still uni-directional in nature, the direction of the effect was unexpected. Better caregiver physical health prospectively predicted *lower* use of adaptive SCE strategies. It may be that physically healthy caregivers experience relatively less negative emotion, and thus report less use of any type of ER strategy (including positive strategies). This is consistent with the DIS and physical health findings (discussed below) showing that physically healthier caregivers also report less use of maladaptive strategies as well. Replication of this finding would be useful before further considerations of such effects and possible explanations, as this unexpected effect had the lowest relative estimate (small effect of -.06) of the five SCE models tested. More future study of relations between adaptive ER strategies and physical health are needed.

There was more variability in the temporal patterns and direction of influence between the DIS factor and adjustment outcomes in the current sample. Caregivers reporting better physical health showed a significantly lower likelihood of relying on maladaptive ER strategies such as avoidance, denial, and wishful thinking at later timepoints. Higher DIS was also associated with lower physical health concurrently around the time of diagnosis, as well as at 6 months post-diagnosis. These findings build on emerging evidence which supports the notion that ER is associated with physical health outcomes (Gross, 2013; Appleton, 2013). The temporal aspect of these results suggests that caregivers of children with cancer struggling with their own physical health symptoms may be significantly more vulnerable to relying on maladaptive ER strategies as time goes on, compared to their physically healthy counterparts. Conversely, physically healthy caregivers are prospectively protected from developing patterns of emotion regulation and coping that are known to be ineffective and potentially psychologically harmful. Interventions that include components which promote caregiver physical health in this population may show positive downstream effects by also improving caregivers' ability to regulate emotion, thereby protecting them from an even broader range of psychological stress and adjustment difficulties. This indirect path to fostering caregiver ER through supporting their physical health is likely to have positive downstream effects on children and broader family adjustment. Physically healthier caregivers who use and model effective (rather than ineffective) ER strategies are more likely to be more effective and responsive parents. Indeed, Crandall, Deater-Deckard, and Riley's (2015) review on parental ER has emphasized the necessity for parents to be adept at regulating their own emotions to effectively support their children's healthy development.

In contrast to the hypothesis that adjustment factors prospectively predict ER, the reverse pattern of DIS prospectively predicting adjustment factors during the first six months were observed for symptoms of depression, anxiety, and PTSS. This suggests that caregivers engaging in higher DIS strategies around the time of diagnosis were those reporting significantly higher depression, anxiety, and PTSS at 6 months post-diagnosis. With regard to temporal patterns, these findings are consistent with previous longitudinal studies that suggest maladaptive ER is a risk factor for the development of psychopathology (McLaughlin, Hatzenbuehler, Mennin, & Nolen-Hoeksema, 2011; McLaughlin & Hatzenbuehler, 2009; McLaughlin, Hatzenbuehler, & Hilt, 2009; Hatzenbuehler, McLaughlin, & Nolen-Hoeksema, 2008; Michl, McLaughlin, Shepherd, & Nolen-Hoeksema, 2013). Thus, interventions which support caregivers in finding more adaptive ways of managing their emotion and stress at the time of diagnosis can help significantly promote their psychological adjustment during the first six months of their child's treatment. Such interventions should include teaching ER strategies which serve as alternatives to avoidance, wishful thinking, and denial, as well as provide psychoeducation and teaching about the potential ongoing harm of relying on DIS ER strategies.

Several unexpected longitudinal findings were observed. Higher treatment related stress, depression, and PTSS at the time of diagnosis prospectively predicted *lower* use of DIS strategies at 6 months. This effect was also statistically significant for higher treatment related stress at 6 months predicting lower DIS at 12 months. Although these effects did not reach statistical significance in the anxiety and DIS model, or between times 6 and 12 for PTSS and

DIS, the direction and magnitude of these paths was consistent with those that did reach significance, suggesting a relatively uniform pattern across these models. Although these unexpected effects were small in size (between -.05 to -.08), their consistency across most DIS models encourages future research to help explain why worse adjustment in some cases predicts less use of maladaptive ER strategies. Future work in this line of research should test other variables that may be related to DIS, to assess whether these paradoxical effects are still present when DIS variance associated with other predictors is accounted for. For instance, some authors have recommended that research on coping and regulatory processes in caregivers of children with cancer should carefully consider the phase of cancer treatment that a family is in, given the significant change in such a stressor over time (Goldbeck, 2001; Trask et al., 2003). Vrijmoet-Wiersma et al., (2008) suggest that the adaptive value of any given ER strategy may depend on the phase of cancer. These authors have suggested that avoidance may be functional in the early phase of the child's cancer when parents are at risk of being overwhelmed with emotion. But at the active treatment and maintenance stage, avoidance loses its adaptive value and instead has been shown to be associated with parental anxiety and depression (Hoekstra-Weebers et al., 1999; Lindahl-Norberg, Lindblad, & Boman, 2005). Although the current data do not speak to such a process, future work should aim to examine whether the utility and function of specific ER strategies changes as a function of the phase of cancer treatment. Such research efforts would be in line with the broader push for ER research to assess how context influences the effectiveness of ER strategies (Aldao & Nolen-Hoeksema, 2012; Bonnano & Burton, 2013). Building on the current work by identifying and including relevant context level predictors into the current models may help better illuminate the current results, including clarifications of these unexpected patterns between worse adjustment prospectively predicting less reliance on maladaptive ER strategies.

A very clear pattern emerged in the current study regarding concurrent associations between ER and adjustment. No concurrent relations between SCE and adjustment factors of depression, anxiety, PTSS, treatment related stress, and physical health were found. The lack of cross sectional associations as well as the lack of prospective relations between SCE and adjustment outcomes in our sample is unexpected, given prior research supporting the link between SCE strategies such as cognitive restructuring and acceptance and psychological health, physical health, and stress (Aldao et al., 2010; Appleton et al., 2013; Gratz & Gunderson, 2006). Moreover, cognitive reappraisal and acceptance are strategies that are prominently featured in cognitive behavioral and acceptance based treatments (Hofmann & Asmundson, 2008). Thus, it is surprising that how much reappraisal, acceptance, or distraction strategies are utilized by caregivers at any given time is not associated with their treatment related stress, nor their psychological or physical health.

In contrast, strong concurrent associations between the DIS factor and all adjustment outcomes were observed, suggesting that higher use of DIS strategies was consistently associated with higher reports of depression, anxiety, PTSS, treatment related stress, and poor physical health. These findings are consistent with a substantial literature emphasizing the co-occurrence of maladaptive approaches to regulating emotion and symptoms of anxiety, depression, and PTSS (Aldao & Nolen-Hoeksema, 2010; Aldao et al., 2010; Kring & Sloan, 2010; Sheppes et al., 2015). It is clear that difficulties with regulating emotion, and specifically reliance on ER strategies such as avoidance, denial, and wishful thinking co-occurs with and probably maintains psychopathology. In regard to treatment related stress, current findings are in line with previous research showing that higher use of ER strategies such as rumination and negative cognitive appraisals are associated with higher stress levels (Martin & Dahlen, 2005). Clinical research to date has emphasized the study of relations between ER and specific symptoms of psychopathology, and thus possibly overlooked other markers of psychological well-being such as stress. The current findings extend ER research by suggesting that individuals experiencing higher treatment related stress are those who are most likely to be engaging in avoidance, wishful thinking, and denial as a way to cope with and manage their emotions. In the context of pediatric cancer, managing the stress associated with the child's diagnosis and treatment may be one of the most important goals and markers of functioning for caregivers. Thus, teaching and supporting caregivers to successfully utilize more adaptive ER strategies and to steer clear of maladaptive strategies may greatly support caregivers' abilities to respond effectively in the face of stress stemming from the intensive process of their child's medical treatment.

The discrepancy in results between SCE and DIS factors, both prospectively and cross-sectionally, are in line with previous research showing that maladaptive strategies are more strongly associated with psychopathology compared to adaptive strategies, both in regard to internalizing (e.g. depression and anxiety) and externalizing issues (e.g., substance use, eating disorders). Specifically, Aldao, Nolen-Hoeksema, & Schweizer's (2010) meta-analytic work found a large effect size for rumination, a medium to large effect size for avoidance, problem solving, and suppression, and small to medium effect sizes for cognitive reappraisal and acceptance. Similarly, stronger associations between maladaptive compared to adaptive ER strategies with psychopathology have also been found in a study of individuals with social anxiety disorder (Aldao et al., 2014) and another study using an undergraduate sample (Aldao & Nolen-Hoeksema, 2010). Thus, it may be much more useful to target assessment, prevention, and intervention efforts for caregivers of children with cancer by aiming to decrease reliance on maladaptive strategies as opposed to just bolstering the use of adaptive strategies. In a follow up study, Aldao & Nolen-Hoeksema (2011) also found that the cross-sectional relation between adaptive ER strategies and psychopathology is moderated by levels of maladaptive strategies. That is, adaptive strategies are only negatively associated with psychopathology at high levels of maladaptive strategies. These interaction effects were also replicated with a clinical sample of 71 participants undergoing cognitive behavioral therapy for social anxiety disorder (Aldao et al., 2014). Thus, one future step in the current line of research around ER in caregivers of children with cancer would be to examine such moderator effects to potentially uncover conditions under which adaptive ER strategies are more predictive of adjustment. Some authors have gone as far as to say that the idea of ER strategies being categorized as adaptive or maladaptive is a myth (Kashdan, Young, & Machell, 2015). As an alternative to measuring the likelihood of engaging in healthy or unhealthy ER strategies, assessing individual differences in ER *flexibility* may be another useful area for future studies to examine (Bonnano & Burton, 2013). It may be that individuals with narrow and rigid ER strategy repertoires are most at risk of maladjustment, and those who are able to flexibly shift their strategies across contexts to find one that works are most protected.

Auto-regressive effects. The current study found a consistent pattern in regard to auto-regressive effects across both ER as well as all adjustment outcomes. Results showed that previous levels of each substantive variable were significantly associated with future levels of the same variable. For instance, how much depression a caregiver reports at a given time is a strong predictor of their depression symptoms measured 6 months later. This is also true for both SCE and DIS ER strategies, suggesting that there is a relatively high level of rank order stability in both ER, psychopathology, treatment related stress, and physical health for caregivers of children with cancer during the first year of treatment. It is important to note that a high level of rank order stability across the first year speaks only to between person differences and does not shed light on how much (if at all) individuals' ER and adjustment scores change across repeated measures (i.e., within person changes). Specifically, this finding means that caregivers who are high on a variable relative to other caregivers at one timepoint are still likely to be high on the variable relative to other caregivers at the next timepoint. Other methods such as multi-level modeling (MLM) (see Katz, et al., 2018; Fladeboe et al., 2017; Lavi et al., 2018), or latent change score (LCS) modeling can be utilized to gain insight into within person change.

In summary, maladaptive ER strategies seem to function primarily as risk factors for psychopathology symptoms, specifically anxiety, PTSS, and depression. Maladaptive strategies also show the strongest associations with adjustment outcomes, both prospectively as well as cross-sectionally, including cross sectional relations with treatment related stress and physical health. In contrast, adaptive strategies appear to be consistently *predicted by* rather than predictive of adjustment, and show relatively weak or non-existent prospective or cross-sectional relations with adjustment. Unexpected evidence was found suggesting that poorer caregiver adjustment at the time of diagnosis predicts less prospective use of maladaptive strategies, and that better physical health prospectively predicts *lower* use of adaptive strategies. Thus, although longitudinal associations between ER and adjustment outcomes showed pre-dominantly uni-directional patterns, the variability in the direction of influence between adaptive and maladaptive strategies, and the handful of transactional patterns suggest a complex bi-directional relation between these factors. Follow up investigation of potential interaction effects between SCE and DIS strategies predicting adjustment may reveal a clearer understanding of relations found in the current study. Other variables such as those related to the child's illness, treatment phase, or other contextual factors should also be examined in follow up work to help understand the complex relations between caregiver adjustment and ER during the first year of treatment. Future empirical and theoretical work should aim to define more fine grained models of ER strategies, and disentangle when specific strategies or groups of strategies work, for whom, and under what conditions.

These findings make a strong case for divergent effects of adaptive vs. maladaptive ER strategies in caregivers of children with cancer. For treatment goals of preventing and managing psychopathology in this population, intervention and prevention programs would do well to assess and prevent caregivers regulating emotion using disengagement strategies such as avoidance, wishful thinking, and denial. For treatment efforts aimed at bolstering adaptive ER skills such as acceptance, cognitive restructuring, positive thinking, and distraction in this population, finding ways to decrease treatment related stress and symptoms of psychopathology would likely be an effective approach. Health care services that are ultimately sensitive to both the negative as well as positive dimensions of ER, and the range of outcomes they can be associated with in this high stress population will be best equipped to support such families. Fortunately, a number of empirically supported ER based interventions, including emotion regulation therapy (Mennin & Fresco, 2014), dialectical behavior therapy (Neacsiu et al., 2014), and affect regulation training (Berking & Schwartz, 2014) can be employed and tailored to the context of pediatric cancer. Given the range of intense and painful emotions that caregivers of children with a life threatening illness face during diagnosis, treatment, and beyond, emotion regulation focused intervention components may be particularly useful for supporting healthy child, caregiver, and family adjustment.

Aim 3: Latent Change Score Modeling of Relations Between ER & Adjustment

We aimed to estimate latent change score (LCS) models to understand specifically how relations between ER and adjustment in caregivers of children with cancer unfold over the first year of treatment. These models combine the ability to assess change (growth or decline) over time, with the ability to specify and test interrelations between variables (Ferrer & McArdle, 2010). Although cross lagged models of Aim 2 begin to lend insights into temporal relations, they primarily speak to rank order stability and between person differences. Cross lagged models do not provide information about within person change and are limited in their ability to model dynamic causal patterns between variables (Selig & Little, 2012). Thus, in regard to questions about temporal associations and dynamics between ER and adjustment, we specifically sought to examine the following questions using LCS models in Aim 3: 1) Is the amount of change in ER related to the amount of change in adjustment? 2) Is the level of ER at a given time point related to the subsequent amount of *change* in adjustment? (3) Is the level of an adjustment factor at a given time point related to the amount of subsequent *change* in ER? (4) What are the leading/lagging relations between ER and adjustment outcomes? and (5) What are the leading/lagging relations between *changes* in ER and changes in adjustment?

The LCS models tested in Aim 3 overall failed to successfully estimate using the current data. Although univariate proportional, constant change, and dual change models appeared to estimate, fit index values fell outside the range of expected values, suggesting that the current sample is underpowered to reliably fit such models to the data. Given the estimation problems with the univariate models, it was not surprising that the originally proposed bivariate LCS models also failed to estimate. Thus, the current study was not able to address substantive questions that this aim hoped to answer.

Although LCS models can be successfully estimated with a sample size as low as that in the current study (see Grimm et al., 2012), smaller samples may require significantly more repeated observations than three timepoints to properly estimate. For instance, Ferrer et al., (2010) successfully estimated LCS models with a sub-sample as small as n = 28, but with data collected across 12 repeated observations. Even with ideal (no attrition) and appropriately powered data sets (e.g., 1000 observations across 6 timepoints), these models present many misspecification challenges (Clark, Nuttall, & Bowles, 2018). Thus, although LCS models are flexible and conceptually powerful tools, they also present significant limitations and should be used in conjunction with other statistical approaches that are well suited for investigating multivariate change over time.

Limitations

The current study has several limitations that should be discussed. First, the study relied exclusively on caregiver self-report methods and single reporter bias may have influenced the results (Achenbach, Krukoswki, Dumenci, & Ivanova, 2005). Both the ER literature as well as the coping literature has been primarily built on empirical work that has relied on self-reports to assess these constructs (Folkman & Moskowitz, 2004). There are considerable limitations involved in self reports to study relations between ER/coping and relations to symptoms of psychological distress. For instance, such methods are susceptible to shared method variance of self-report in general, reporting biases, confounding of items, and problems with recalling specific ER/coping related behaviors (Compas et al., 2014). Despite this limitation, studies suggest that coping self-report measures can achieve convergence across multiple informants (e.g., parents and children reporting on child coping; Jaser et al., 2005; Compas et al., 2006). Moreover, coping self-report measures like the RSQ have been validated in their relations with a range of important cognitive and physiological measures such as executive functions (e.g., working memory, cognitive flexibility, behavioral inhibition, and self-monitoring; Campbell et al., 2009; Andreotti et al., 2013). Nonetheless, observed relations between ER and adjustment factors of psychopathology, health, and treatment related stress may be biased by the same individual reporting on each. Given the potential overlap in the primary constructs of interest, particularly that of ER and psychopathology (Bloch, Moran, & Kring, 2010), it may be that caregivers experiencing generally high distress during their child’s treatment are biased to report lower adjustment and ER functioning. Future research should aim to incorporate multiple reporters and multiple methods for assessing ER and adjustment factors to mitigate effects of single reporter bias.

Another limitation of the current study is the relatively low power. Thus, it may be that any null findings were due to a lack of power to detect effects. In addition, this factor limited the ability to properly estimate latent change score models, and thus precluded important insights about the temporal dynamics of change between ER and adjustment factors. Follow up research should aim to examine these questions in larger samples with more repeated observations to increase the study’s capacity to be adequately powered to detect effects.

Finally, another significant limitation includes the amount of post-hoc re-specifications that were conducted during the analytic stage. Although such a data driven approach is not uncommon when diagnosing points of misspecification and error in SEM models, this limits the generalizability of the current findings and these results need replication.

Strengths

The current study also has several noteworthy strengths. This is one of the few studies, to our knowledge, to critically consider and empirically test the temporal sequence between ER and adjustment outcomes. Although a large body of literature supports the role of ER as a transdiagnostic factor underlying a range of mental health and related outcomes, there is surprisingly little work examining ER as an outcome, or studies testing transactional relations between such variables. The current study expands this area of research by examining the question of temporal sequence between these factors as a central research question. Findings suggest that ER is just as likely to be predicted by earlier markers of adjustment, as it is to function as a prospective predictor or risk factor for later adjustment in this population. Thus, future research on ER and adjustment should consider this more complex relationship between ER and psychopathology, stress, and physical health, and move beyond tests of static uni-directional relations to better understand how these variables unfold over time. In addition, adaptive vs. maladaptive strategies may have different functions, and show divergence in regard to whether they are a predictor or a consequence of psychopathology in relation to other adjustment outcomes. Previous ER research which has collapsed such distinctly different ER domains in their conceptualizations and measurement methods may have obscured unique differences in the relations between adaptive vs. maladaptive ER strategies and other variables of interest. Future work should aim to carefully define and evaluate theory driven conceptualizations and measurement models of ER, and investigate both similarities and differences across the variety of ER factors.

Another strength of this study is the diversity of the sample with respect to diagnoses and socio-economic status. This increases the generalizability of the current findings to a broader range of families with children who have various cancer diagnoses and come from various backgrounds. On the other hand, there may be families with children who have specific diagnoses such as brain tumors for whom processes of ER and adjustment may look different, and future studies with large samples may be able to test how effects observed in the current study may vary by diagnosis or other family factors.

Finally, another strength of this study is the conceptually driven specification and evaluation of a measurement model of ER. As many authors have noted, one of the biggest challenges of ER research is the wide variability in measurement methods (Gross, 2013; Bridges, Denham, & Ganniban, 2013). Beginning with work that validates the psychometric qualities of an ER measure strengthens the validity and reliability of any further analyses and findings using the measure. The measurement work done in the current study contributes to strengthening the conceptual and psychometric properties of ER and coping constructs as measured by the RSQ by validating a measurement structure in the current sample that is consistent with previous research. More psychometric work in ER research can help establish the most valid and reliable measures and thereby increase the quality, consistency, and comparability of findings across studies.

Conclusions

The current study highlights the variable longitudinal patterns of influence between ER and psychopathology, treatment related stress, and physical health in caregivers of children with cancer over the first year of treatment. Caregiver adjustment prospectively predicts caregivers' abilities to draw on adaptive ER strategies, whereas adaptive strategies themselves do not appear to predict psychological or physical caregiver symptoms or treatment related stress. In line with the broader ER literature, maladaptive ER strategies concurrently and prospectively predict symptoms of PTSS, anxiety, and depression in this population. The prospective influence of early caregiver adjustment on future use of maladaptive ER strategies is unexpectedly complex and requires more research to fully understand. The current study expands ER research by studying the importance of this transdiagnostic factor in the at risk population of caregivers of children with cancer, as well as examining associations between ER and physical health and stress. These findings also provide increased understanding of the temporal process by which patterns of risk unfold between markers of psychological and physical adjustment and the transdiagnostic factor of ER. Such insights have potential to inform specific targets for psychosocial interventions which can greatly support the psychological and physical well-being of caregivers. Continued work aimed at identifying and testing the most viable and effective targets and methods for intervention has potential to profoundly improve our ability to foster resilience in families of children with cancer.

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Figure 1. Aim 1: Theoretical Models for Measurement Structure of Emotion Regulation

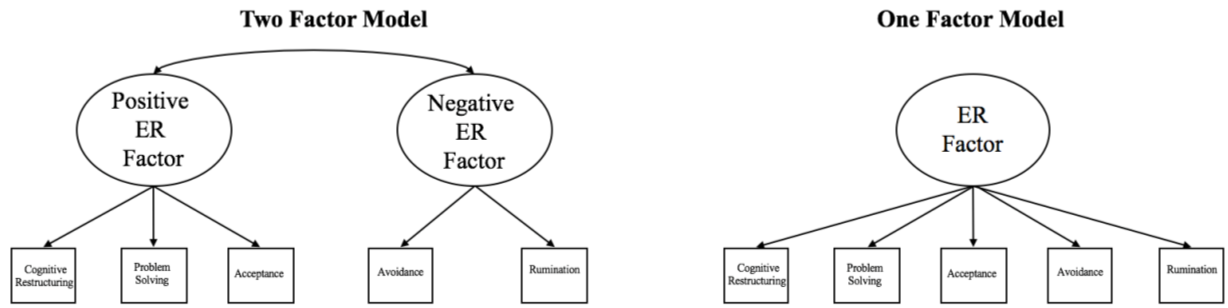


Figure 2. Aim 1: Final Measurement Model of Emotion Regulation

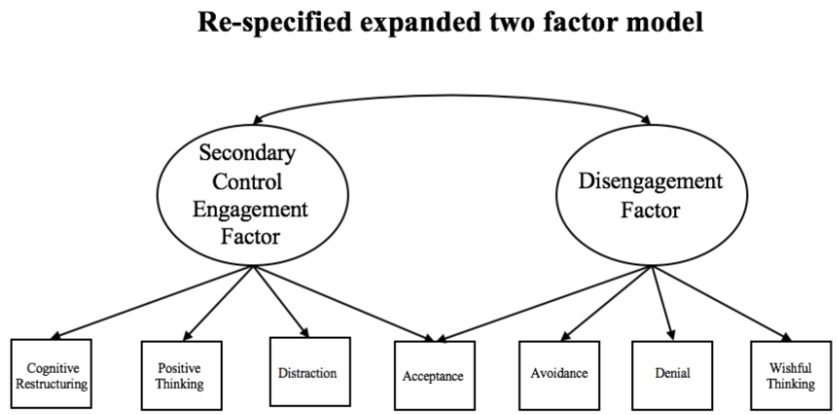


Table 1. Aim 1: Fit Indices for Measurement Models

	Model Fit Information				
Measurement Models	**χ^2 (df), *p* value**	**RMSEA**	**SRMR**	**CFI/TLI**	**AIC/BIC**
Model 1. Two factor model	—	—	—	—	—
Model 2. One factor model	30.60 (5), p = .000	.19	.09	0.61/0.21	2916.91/2960.60
Model 3. Re-specified two factor model	—	—	—	—	—
Model 4. Re-specified one factor model	37.06 (6), p = .000	.20	.105	.52/.20	2921.37/2962.15
Model 5. Expanded two factor model	33.13 (13), p = .002	.11	.077	.92/.88	3805.57/3869.66
Model 6. Re-specified expanded two factor model	19.76 (12), p = .072	.07	.040	.97/.95	3794.22/3861.21

Note. No fit values available for Models 1 and 3 due to model non-convergence.

Table 2. Aim 1: Chi-square Difference Tests of Measurement Invariance Models

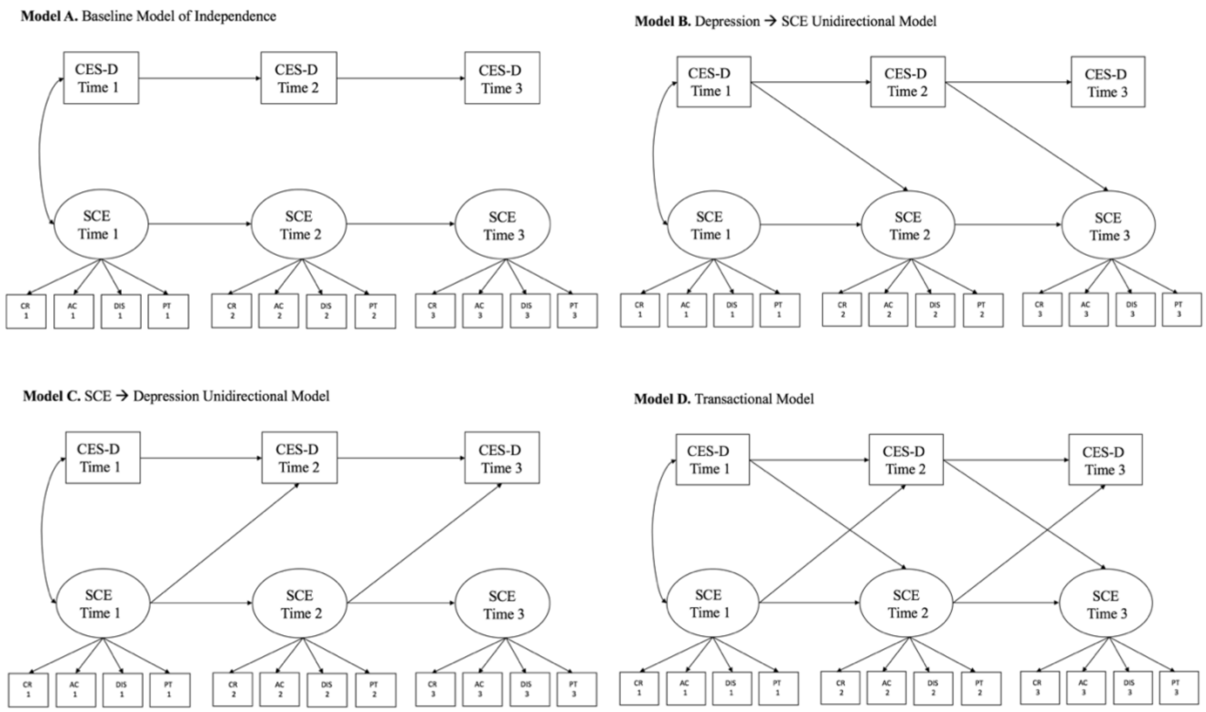
	Df	**AIC**	**BIC**	**X^2**	**X^2 diff**	**Df diff**	***p* value**
Secondary Control Engagement Factor							
Configural	39	3557.92	3677.48	50.01	—	—	—
Metric	45	3556.55	3662.05	60.63	10.62	6	0.10
Scalar	51	3545.64	3637.04	61.72	1.09	6	0.98
Residual	53	3561.05	3647.71	81.11	19.39	2	0.00***
Disengagement Factor							
Configural	39	3520.50	3640.03	46.35	—	—	—
Metric	45	3511.01	3616.49	48.82	2.47	6	0.23
Scalar	51	3516.80	3608.25	66.69	17.87	6	0.08**
Residual	53	3524.86	3611.66	78.70	3.968	2	0.14**
Disengagement Factor Partial Invariance							
Configural	42	3519.15	3631.66	50.92	—	—	—
Metric	46	3512.42	3615.59	52.23	1.32	4	0.85
Scalar	50	3513.13	3606.80	60.92	8.69	4	0.07
Residual	52	3515.98	3604.92	67.73	6.80	2	0.03*

Note. *** < 0.001, ** < .01, * < .05

Table 3. Aim 1: Fit Measures for Measurement Invariance Models

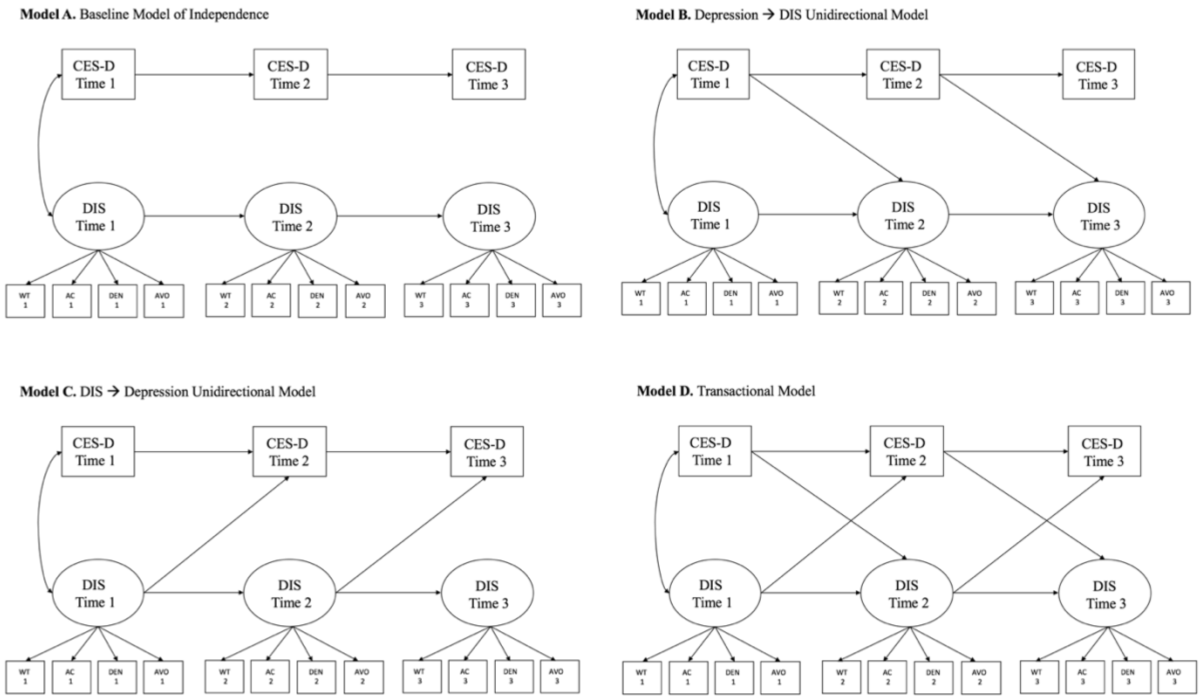
	CFI	**RMSEA**	**ΔCFI**	**ΔRMSEA**
Secondary Control Engagement Factor				
Configural	0.974	0.061	--	--
Metric	0.963	0.067	0.011	0.007
Scalar	0.975	0.052	0.012	0.015
Residual	0.933	0.083	0.041	0.031
Disengagement Factor				
Configural	0.984	0.049	--	--
Metric	0.992	0.033	0.008	0.016
Scalar	0.966	0.063	0.026	0.030
Residual	0.944	0.079	0.022	0.016
Disengagement Factor Partial Invariance				
Configural	0.981	0.053	--	--
Metric	0.986	0.042	0.006	0.011
Scalar	0.976	0.053	0.010	0.011
Residual	0.966	0.063	0.010	0.009

Figure 3. Aim 2: Theoretical models for unidirectional vs. transactional model comparisons for Secondary Control Engagement (SCE) factor



Note. CR = Cognitive Restructuring; AC = Acceptance; DIS = Distraction; PT = Positive Thinking.

Figure 4. Aim 2: Theoretical models for unidirectional vs. transactional model comparisons for Disengagement (DIS) factor



Note. WT = Wishful Thinking; AC = Acceptance; DEN = Denial; AVO = Avoidance.

Table 4. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – SCE & Depression

Model Fit Information - SCE & Depression					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	270.91 (101), .000	.11	.11	.73/.71	7176.24/7276.97
B. Depression → SCE	250.32 (99), .000	.11	.10	.76/.74	7159.64/7266.30
C. SCE → Depression	270.09 (99), .000	.11	.11	.72/.71	7179.41/7286.08
D. Transactional	249.26 (97), .000	.10	.11	.75/.73	7162.58/7275.17

Nested Model Fit Comparisons	
	χ^2_{dif} (df $_{dif}$)
A vs. B	20.60 (2)***
A vs. C	0.82 (2)
A vs. D	21.66 (4)***
B vs. D	1.06 (2)
C vs. D	20.84 (2)***

Note. **p* < .05, ***p* < .01, ****p* < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 5. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – SCE & Anxiety

Model Fit Information - SCE & Anxiety					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	269.91 (101), .000	.117	.108	.717/.706	6836.96/6937.69
B. Anxiety → SCE	257.38 (99), .000	.117	.106	.735/.718	6828.43/6935.09
C. SCE → Anxiety	269.76 (99), .000	.117	.110	.714/.696	6840.81/6947.47
D. Transactional	257.32 (97), .000	.118	.108	.731/.709	6832.37/6944.95

Nested Model Fit Comparisons	
	χ^2_{dif} (df_{dif})
A vs. B	12.53 (2)**
A vs. C	0.15 (2)
A vs. D	12.59 (4)*
B vs. D	0.06 (2)
C vs. D	12.44 (2)**

Note. *p < .05, **p < .01, ***p < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 6. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – SCE & PTSS

Model Fit Information - SCE & PTSS					
Model	χ^2 **(df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	303.72 (101), .000	.12	.12	.70/.68	7769.89/7870.63
B. PTSS → SCE	288.87 (99), .000	.13	.12	.72/.70	7759.03/7865.70
C. SCE → PTSS	302.36 (99), .000	.12	.12	.70/.68	7772.53/7879.19
D. Transactional	287.35 (97), .000	.12	.12	.71/.69	7761.52/7874.11

Nested Model Fit Comparisons	
	χ^2_{dif} **(df $_{dif}$)**
A vs. B	14.86 (2)***
A vs. C	1.36 (2)
A vs. D	16.40 (4)**
B vs. D	1.51 (2)
C vs. D	15.01 (2)***

Note. *p < .05, **p < .01, ***p < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 7. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – SCE & Treatment Related Stress

Model Fit Information - SCE & TRS					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	309.89 (101), .000	.12	.12	.66/.64	7700.27/7801.01
B. TRS $\rightarrow$ SCE	286.63 (99), .000	.11	.12	.69/.67	7681.01/7787.67
C. SCE $\rightarrow$ TRS	309.62 (99), .000	.12	.12	.65/.63	7704.00/7810.66
D. Transactional	286.29 (97), .000	.11	.12	.69/.67	7684.67/7797.25

Nested Model Fit Comparisons	
	χ^2_{dif} (df $_{dif}$)
A vs. B	23.26 (2)***
A vs. C	0.28 (2)
A vs. D	23.61 (4)***
B vs. D	0.35 (2)
C vs. D	23.33 (2)***

Note. **p* < .05, ***p* < .01, ****p* < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 8. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – SCE & Health

Model Fit Information - SCE & Health

Model	χ^2 **(df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	289.32 (101), .000	.12	.11	.70/.69	5765.61/5866.35
B. Health → SCE	263.50 (99), .000	.11	.12	.74/.73	5743.79/5850.45
C. SCE → Health	287.00 (99), .000	.12	.12	.70/.69	5767.29/5873.95
D. Transactional	261.31 (97), .000	.11	.11	.74/.72	5745.60/5858.19

Nested Model Fit Comparisons

	χ^2_{dif} **(df** $_{dif}$**)**
A vs. B	25.82 (2)***
A vs. C	2.32 (2)
A vs. D	28.02 (4)***
B vs. D	2.19 (2)
C vs. D	25.70 (2)***

Note. **p* < .05, ***p* < .01, ****p* < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 9. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – DIS & Depression

Model Fit Information - DIS & Depression

Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	308.27 (99), .000	.15	.12	.74/.72	7152.16/7258.82
B. Depression → DIS	303.01 (97), .000	.16	.12	.74/.72	7150.90/7263.49
C. DIS → Depression	291.49 (97), .000	.12	.12	.76/.74	7139.39/7251.97
D. Transactional	261.31 (95), .000	.12	.12	.77/.74	7134.75/7253.25

Nested Model Fit Comparisons

	χ^2_{dif} (df_{dif})
A vs. B	5.26 (2)
A vs. C	16.77 (2)***
A vs. D	25.42 (4)***
B vs. D	20.17 (2)***
C vs. D	8.65 (2)*

Note. **p* < .05, ***p* < .01, ****p* < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 10. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – DIS & Anxiety

Model Fit Information - DIS & Anxiety					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	295.53 (99), .000	.16	.12	.74/.73	6818.41/6925.07
B. Anxiety → DIS	294.35 (97), .000	.16	.12	.74/.72	6821.24/6933.82
C. DIS → Anxiety	275.08 (97), .000	.12	.11	.77/.75	6801.96/6914.55
D. Transactional	272.90 (95), .000	.12	.11	.77/.74	6803.78/6922.29

Nested Model Fit Comparisons	
	χ^2_{dif} (df $_{dif}$)
A vs. B	1.17 (2)
A vs. C	20.45 (2)***
A vs. D	22.63 (4)***
B vs. D	21.46 (2)***
C vs. D	2.18 (2)

Note. *p < .05, **p < .01, ***p < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 11. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – DIS & PTSS

Model Fit Information - DIS & PTSS					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	320.86 (99), .000	.15	.13	.75/.73	7700.86/7807.52
B. PTSS → DIS	314.90 (97), .000	.15	.13	.75/.73	7698.90/7811.49
C. DIS → PTSS	297.88 (97), .000	.12	.12	.77/.75	7861.88/7794.64
D. Transactional	272.90 (95), .000	.12	.12	.78/.76	7674.11/7792.63

Nested Model Fit Comparisons	
	χ^2_{dif} (df_{dif})
A vs. B	5.96 (2)
A vs. C	22.98 (2)***
A vs. D	34.74 (4)***
B vs. D	28.79 (2)***
C vs. D	11.76 (2)**

Note. **p* < .05, ***p* < .01, ****p* < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 12. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – DIS & Treatment Related Stress

Model Fit Information - DIS & TRS					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	312.08 (99), .000	.15	.12	.71/.69	7692.66/7799.33
B. TRS → DIS	299.49 (97), .000	.15	.12	.73/.70	7684.07/7796.66
C. DIS → TRS	302.33 (97), .000	.12	.12	.72/.70	7686.92/7799.50
D. Transactional	287.95 (95), .000	.12	.12	.74/.71	7676.54/7795.05

Nested Model Fit Comparisons	
	χ^2_{dif} (df $_{dif}$)
A vs. B	12.59 (2)**
A vs. C	9.75 (2)**
A vs. D	24.13 (4)***
B vs. D	11.54 (2)**
C vs. D	14.38 (2)***

Note. *p < .05, **p < .01, ***p < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

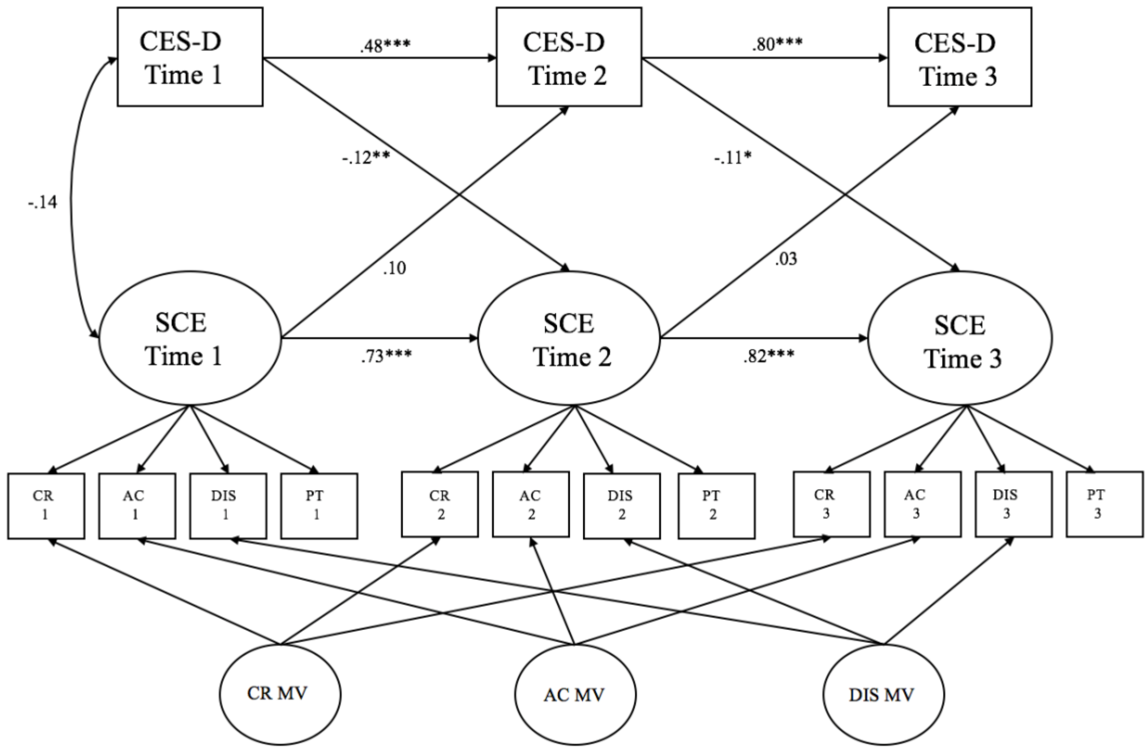
Table 13. Aim 2: Model Fit and Chi-square Difference Tests for Nested Models – DIS & Health

	Model Fit Information - DIS & Health				
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Baseline	294.15 (99), .000	.14	.12	.75/.73	5759.26/5865.93
B. Health → DIS	280.44 (97), .000	.13	.12	.76/.74	5749.56/5862.14
C. DIS → Health	285.62 (97), .000	.12	.12	.75/.73	5754.74/5867.33
D. Transactional	272.15 (95), .000	.12	.11	.77/.75	5745.26/5863.77

Nested Model Fit Comparisons	
	χ^2_{dif} (df $_{dif}$)
A vs. B	13.71 (2)**
A vs. C	8.53 (2)*
A vs. D	22.00 (4)***
B vs. D	8.29 (2)*
C vs. D	13.48 (2)**

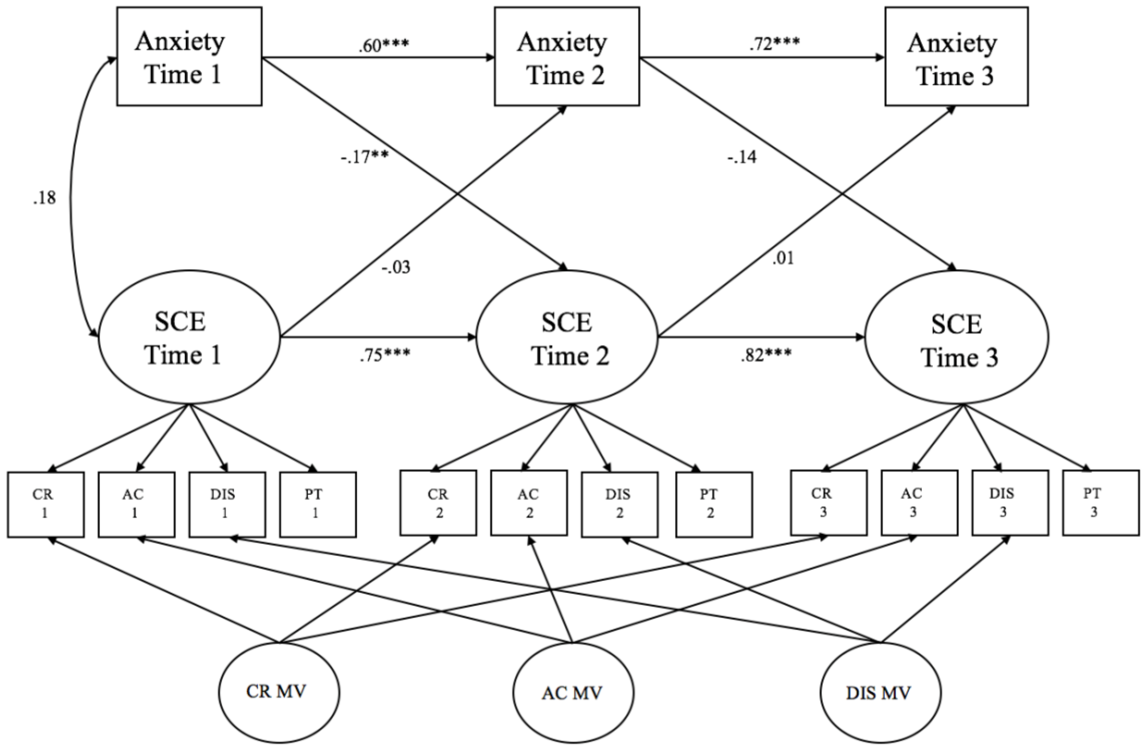
Note. *p < .05, **p < .01, ***p < .001. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Figure 5. Aim 2: Final SCE & Depression Model



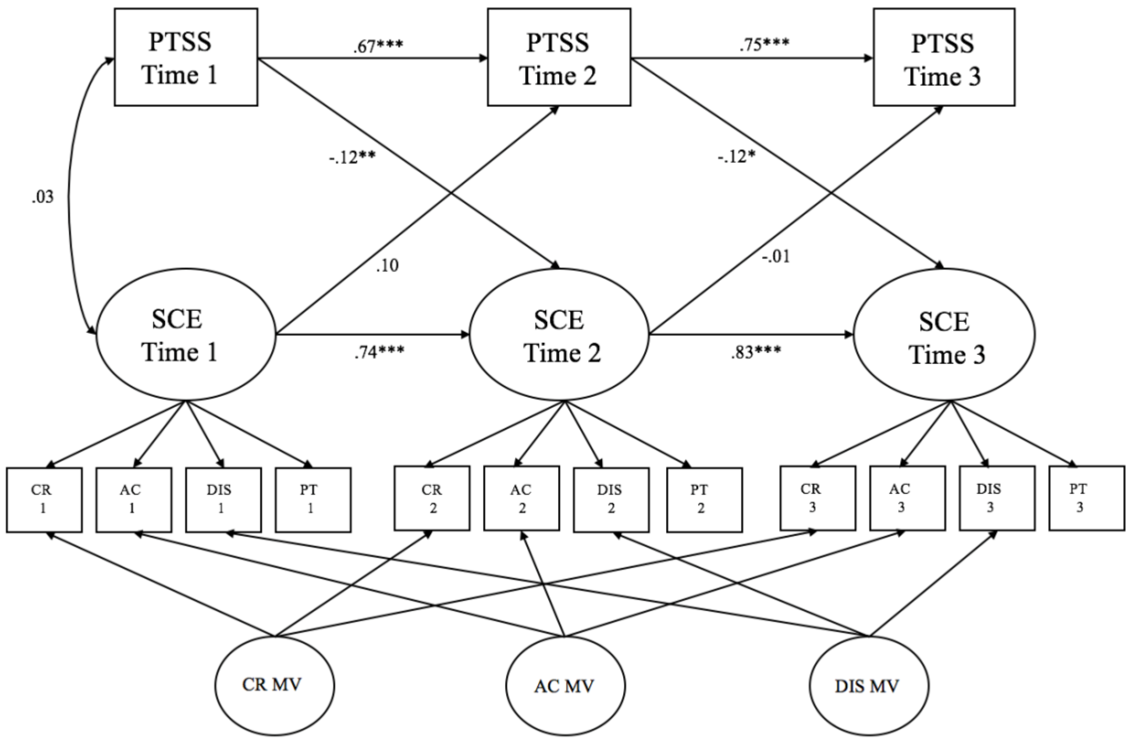
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. CR = Cognitive Restructuring; AC = Acceptance; DIS = Distraction; PT = Positive Thinking; MV = method variance factor.

Figure 6. Aim 2: Final SCE & Anxiety Model



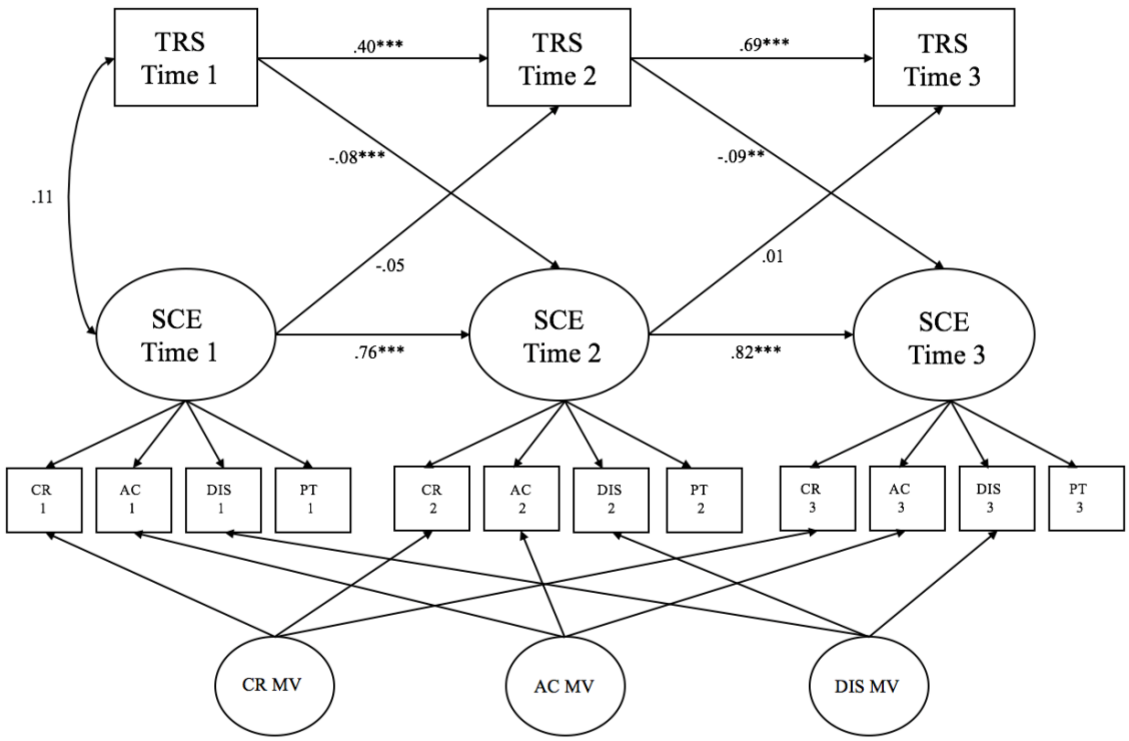
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. CR = Cognitive Restructuring; AC = Acceptance; DIS = Distraction; PT = Positive Thinking; MV = method variance factor.

Figure 7. Aim 2: Final SCE & PTSS Model



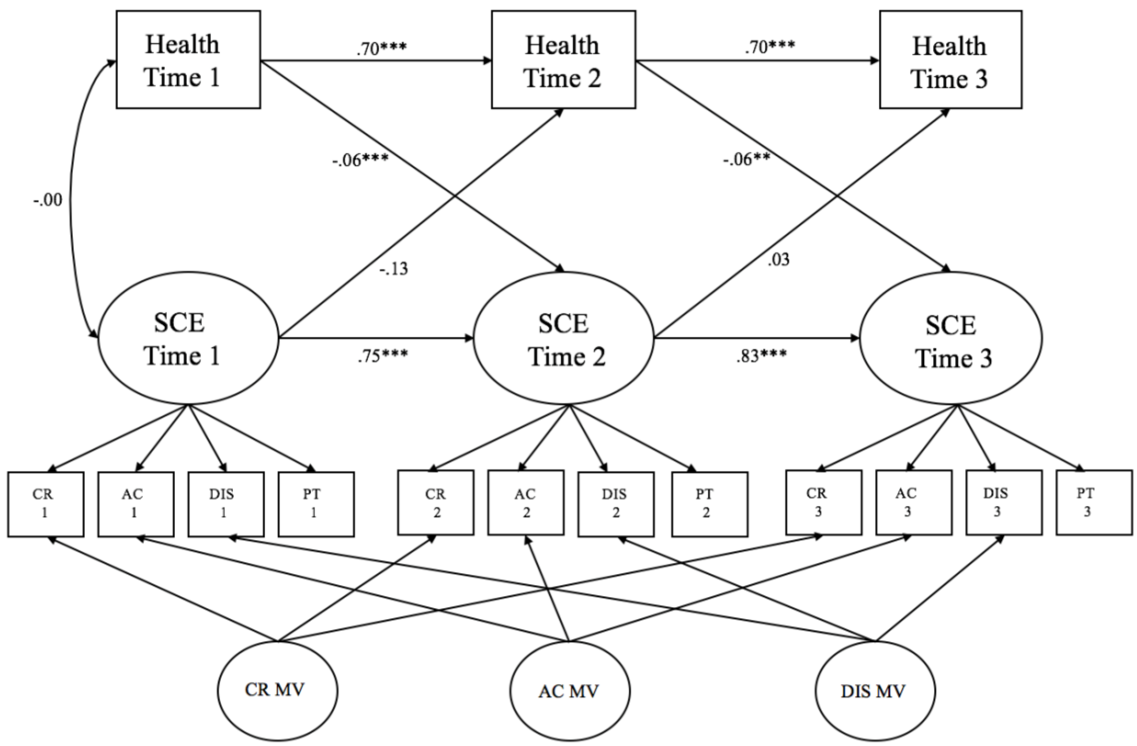
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. CR = Cognitive Restructuring; AC = Acceptance; DIS = Distraction; PT = Positive Thinking; MV = method variance factor.

Figure 8. Aim 2: Final SCE & TRS Model



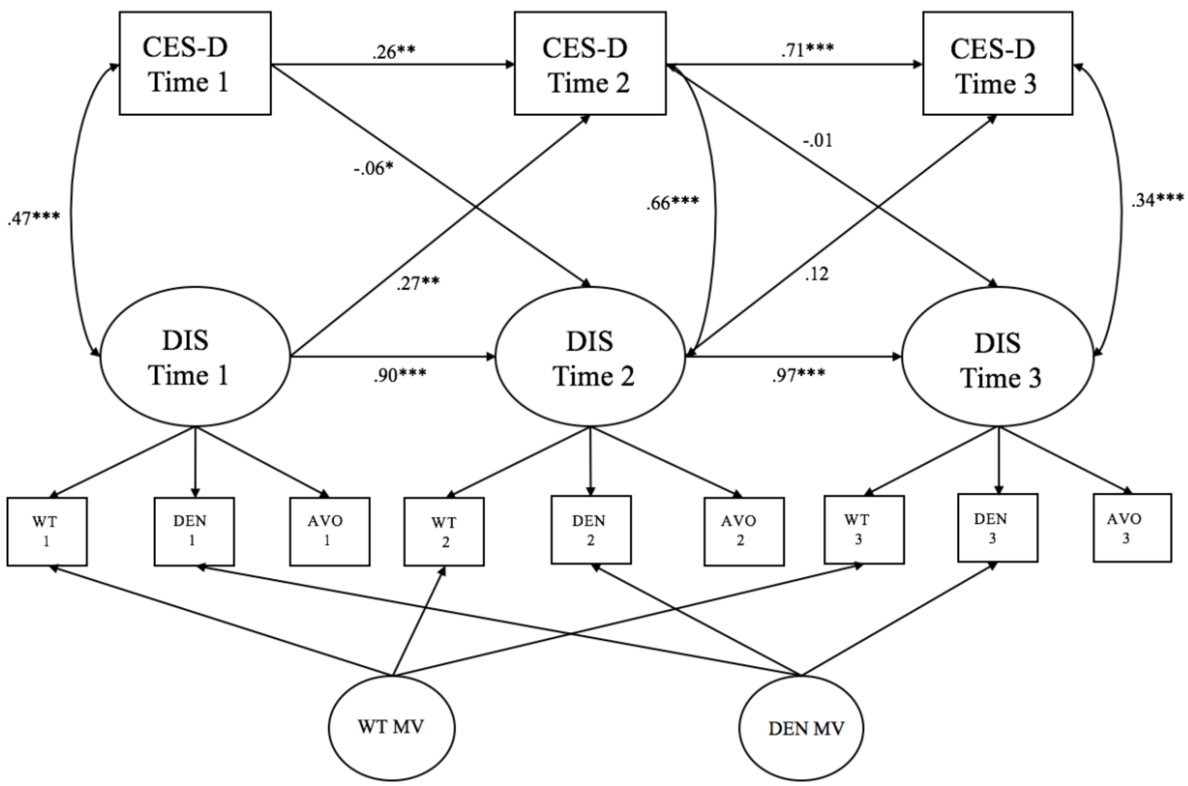
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. CR = Cognitive Restructuring; AC = Acceptance; DIS = Distraction; PT = Positive Thinking; MV = method variance factor.

Figure 9. Aim 2: Final SCE & Health Model



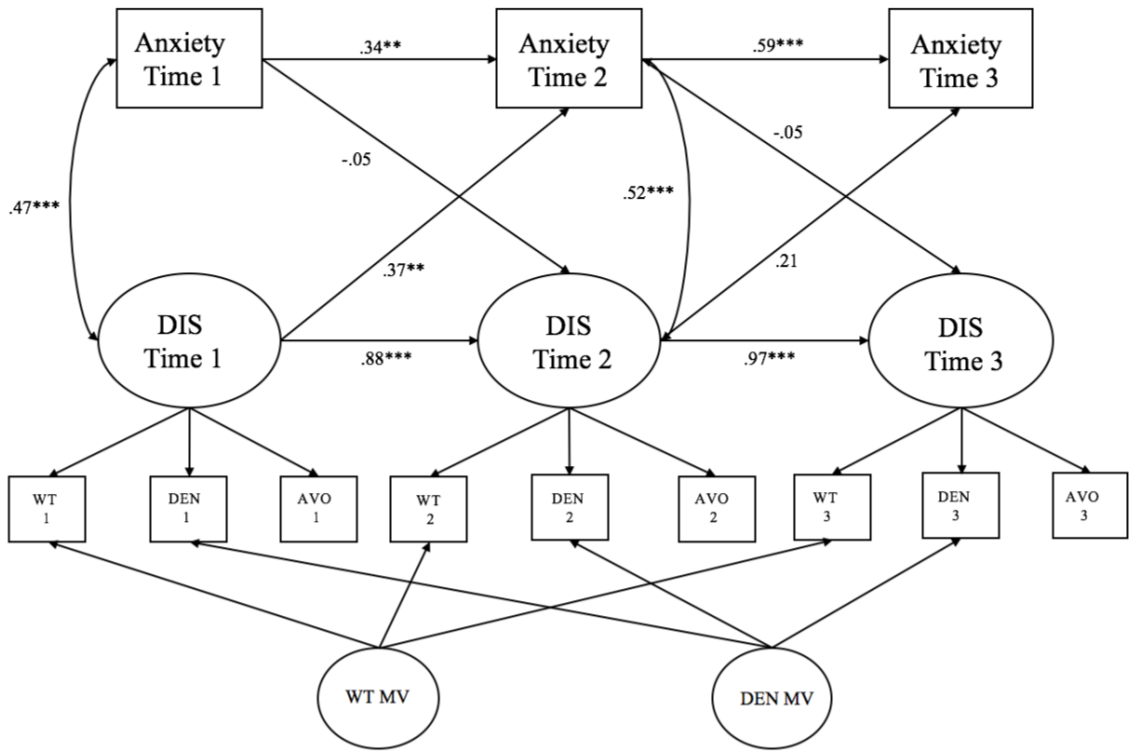
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. CR = Cognitive Restructuring; AC = Acceptance; DIS = Distraction; PT = Positive Thinking; MV = method variance factor.

Figure 10. Aim 2: Final DIS & Depression Model



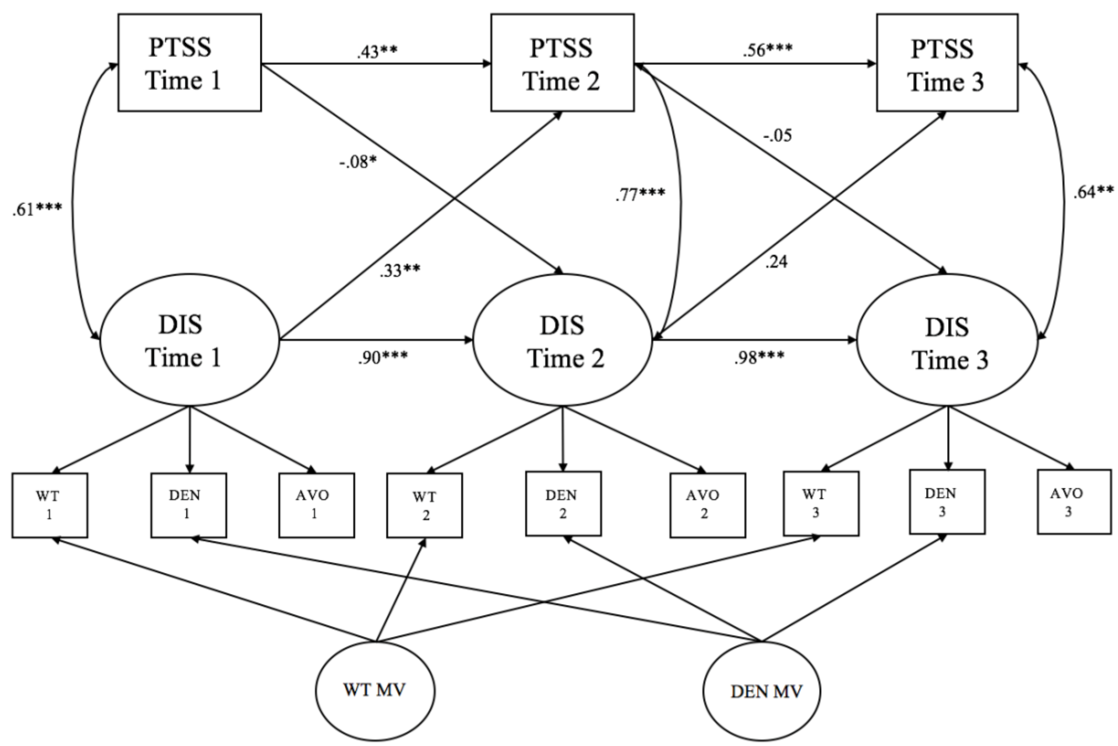
Note. Figure contains standardized path estimates. *p < .05, **p < .01, ***p < .001. WT = Wishful Thinking; DEN = Denial; AVO = Avoidance; MV = method variance factor.

Figure 11. Aim 2: Final DIS & Anxiety Model



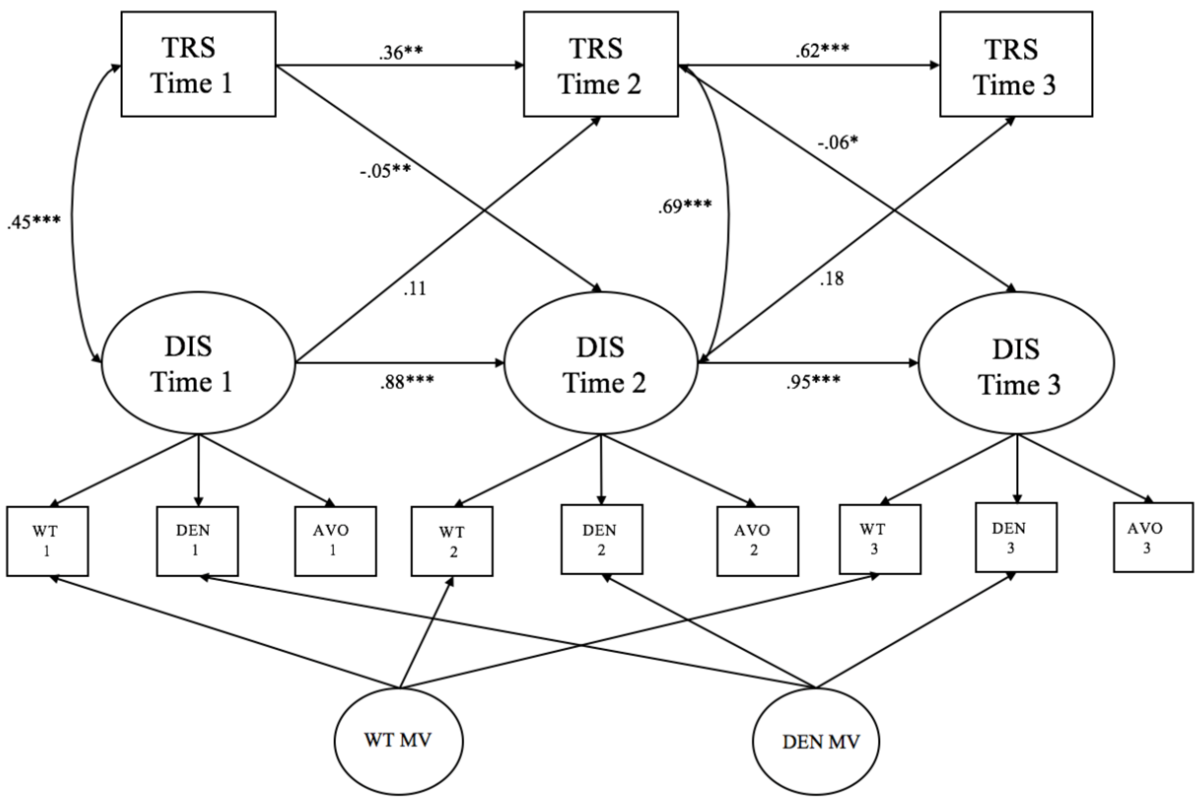
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. WT = Wishful Thinking; DEN = Denial; AVO = Avoidance; MV = method variance factor.

Figure 12. Aim 2: Final DIS & PTSS Model



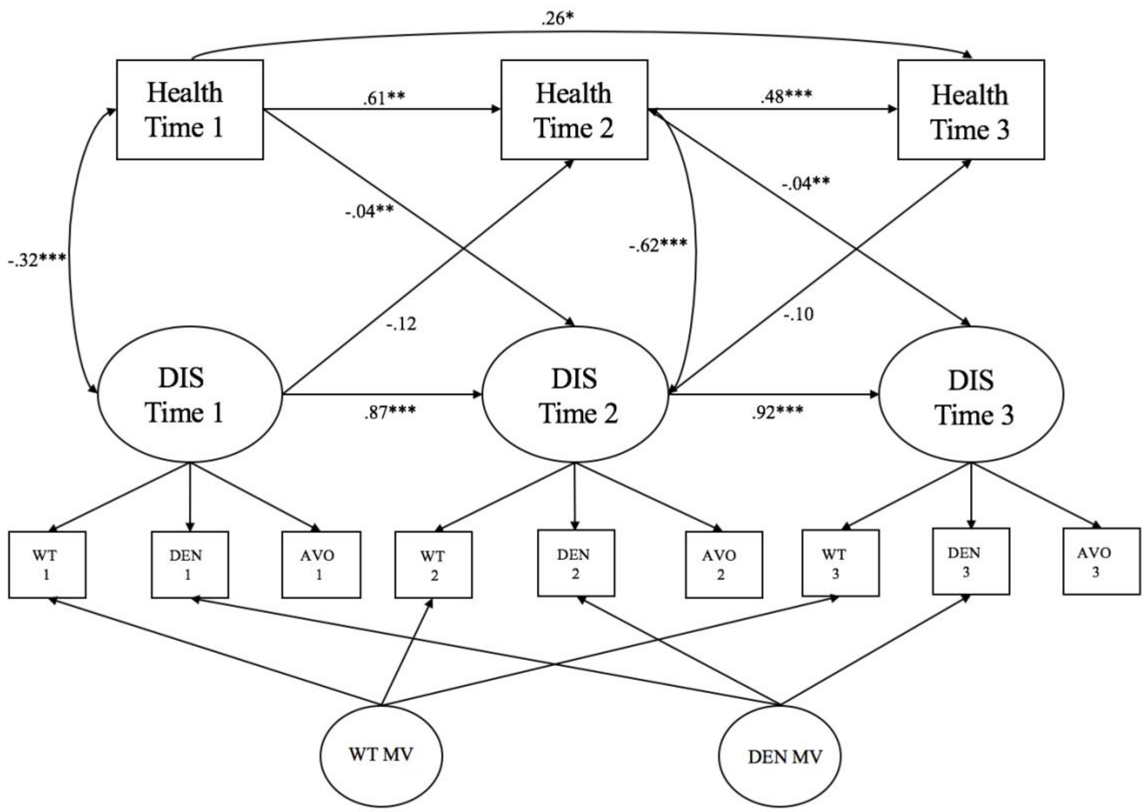
Note. Figure contains standardized path estimates. **p* < .05, ***p* < .01, ****p* < .001. WT = Wishful Thinking; DEN = Denial; AVO = Avoidance; MV = method variance factor.

Figure 13. Aim 2: Final DIS & TRS Model



Note. Figure contains standardized path estimates. *$p < .05$, **$p < .01$, ***$p < .001$. WT = Wishful Thinking; DEN = Denial; AVO = Avoidance; MV = method variance factor.

Figure 14. Aim 2: Final DIS & Health Model



Note. Figure contains standardized path estimates. *$p < .05$, **$p < .01$, ***$p < .001$. WT = Wishful Thinking; DEN = Denial; AVO = Avoidance; MV = method variance factor.

Table 14. Summary of Temporal Patterns & Direction of Effects Between ER & Adjustment Variables

	ER Factor	
Adjustment Variable	**Secondary Control Engagement (SCE)**	**Disengagement (DIS)**
Depression	Uni-directional: **Depression → SCE**	Transactional: *Depression → DIS** *DIS → Depression*
Anxiety	Uni-directional: *Anxiety → SCE*	Uni-directional: *DIS → Anxiety*
PTSS	Uni-directional: **PTSS → SCE**	Transactional: *PTSS → DIS** *DIS → PTSS*
Treatment Related Stress	Uni-directional: **TRS → SCE**	Uni-directional: **TRS → DIS***
Physical Health	Uni-directional: **Health → SCE***	Uni-directional: **Health → DIS**

Note. *Italics* = pattern of effects found only for the first six months; Bold = pattern of effects found across full 12 months; ***** = Unexpected direction of effect

Table 15. Aim 3: Model Fit for Univariate Latent Change Score Model – Secondary Control Engagement (SCE)

	Model Fit Information – Secondary Control Engagement				
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proportional Change Model	8.30 (5) .14	.05	.07	.97/.98	830.87/842.64
B. Constant Change Model	1.21 (3) .75	.04	.00	1.00/1.02	827.78/845.43
C. Dual Change Model	.97 (2) .62	.03	.00	1.00/1.00	829.53/850.12
D. Changes-to-Changes Model	—	—	—	—	—

Note. Fit statistics unavailable for Changes-to-Changes Model due to model non-convergence. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 16. Aim 3: Model Fit for Univariate Latent Change Score Model – Disengagement (DIS)

Model Fit Information - Disengagement					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proportional Change Model	5.95 (5) .31	.05	.04	.99/.99	837.06/848.82
B. Constant Change Model	4.72 (3) .19	.04	.06	.98/.98	839.84/857.49
C. Dual Change Model	1.50 (2) .47	.04	.00	1.00/1.01	838.61/859.20
D. Changes-to-Changes Model	—	—	—	—	—

Note. Fit statistics unavailable for Changes-to-Changes Model due to model non-convergence. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 17. Aim 3: Model Fit for Univariate Latent Change Score Model – Depression

Model Fit Information - Depression					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proprotional Change Model	24.39 (5), .00	.09	.17	.81/.88	845.62/857.39
B. Constant Change Model	19.53 (3), .00	.08	.20	.84/.84	844.75/862.40
C. Dual Change Model	.29 (2), .87	.01	.00	1.00/1.03	827.52/848.11
D. Changes-to-Changes Model	.29 (1), .59	.01	.00	1.00/1.02	829.52/853.05

Note. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 18. Aim 3: Model Fit for Univariate Latent Change Score Model – Anxiety

	Model Fit Information - Anxiety				
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proprotional Change Model	5.36 (5), .37	.05	.02	1.00/1.00	835.76/847.56
B. Constant Change Model	2.37 (3), .50	.03	.00	1.00/1.01	836.77/854.47
C. Dual Change Model	1.50 (2), .47	.01	.00	1.00/1.02	836.95/857.59
D. Changes-to-Changes Model	.55 (1), .46	.02	.00	1.00/1.02	838.95/862.54

Note. Fit statistics unavailable for Changes-to-Changes Model due to model non-convergence. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 19. Aim 3: Model Fit for Univariate Latent Change Score Model – PTSS

	Model Fit Information - PTSS				
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proprotional Change Model	7.09 (5), .21	.04	.05	.98/.99	809.85/821.68
B. Constant Change Model	.91 (3), .82	.02	.00	1.00/1.02	807.68/825.41
C. Dual Change Model	.65 (2), .72	.02	.00	1.00/1.02	809.41/830.11
D. Changes-to-Changes Model	.65 (1), .42	.02	.00	1.00/1.01	811.41/835.06

Note. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 20. Aim 3: Model Fit for Univariate Latent Change Score Model – Treatment Related Stress

Model Fit Information – Treament Related Stress					
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proprotional Change Model	13.56 (5), .02	.08	.11	.84/.90	797.17/808.88
B. Constant Change Model	8.27 (3), .04	.07	.11	.90/.90	795.87/813.44
C. Dual Change Model	.89 (2), .64	.02	.00	1.00/1.03	790.50/810.99
D. Changes-to-Changes Model	.89 (1), .35	.02	.00	1.00/1.01	792.50/815.91

Note. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.

Table 21. Aim 3: Model Fit for Univariate Latent Change Score Model – Health

	Model Fit Information - Health				
Model	**χ^2 (df), *p* value**	**SRMR**	**RMSEA**	**CFI/TLI**	**AIC/BIC**
A. Proprotional Change Model	3.74 (5), .59	.03	.00	1.00/1.01	813.69/825.49
B. Constant Change Model	.58 (3), .90	.02	.00	1.00/1.02	814.53/832.22
C. Dual Change Model	.50 (2), .78	.02	.00	1.00/1.02	816.45/837.09
D. Changes-to-Changes Model	.50 (1), .48	.02	.00	1.00/1.01	818.45/842.04

Note. Fit statistics unavailable for Changes-to-Changes Model due to model non-convergence. SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error Approximation; CFI = Comparative Fit Index; TLI = Tucker Lewis Index; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria.