A Longitudinal Examination of Depression Among Older Adults: The Role of Working Memory and Sleep

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A LONGITUDINAL EXAMINATION OF DEPRESSION AMONG OLDER ADULTS: THE ROLE OF WORKING MEMORY AND SLEEP

by

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INTRODUCTION

The development and regulation of depressive symptoms and the ability to regulate their development is a complex process. Both working memory and sleep disturbance relates to depressive symptom endorsement, though the mechanisms relating these variables have not been examined longitudinally. The current manuscript contains a series of three interrelated studies that aim to elucidate the relationship between potential emotion regulation resources longitudinally within the context of the Selection, Optimization, and Compensation of Emotion Regulation (SOC-ER) model. Study one examined the temporal relationship between working memory and depression, study two examined working memory and depression following loss of spouse, and finally, study three examined the relationship between sleep quality, working memory, and depressive symptoms.

METHOD

Participants were drawn from the Health and Retirement Study, which is a longitudinal dataset sponsored by the National Institute on Aging and collected through the University of Michigan. Data have been collected every two years since 1992 and consists of randomly selected participants ages 65 years and older (Hauser & Willis, 2004). Working memory was measured by Serial 7’s, and the 8-question CES-D was used to measure depressive symptoms.

RESULTS

Study one utilized a latent growth model to evaluate the relationship between working memory and depressive symptoms over time. A significant bidirectional rather than a temporal relationship between the two was observed. Furthermore, both depressive symptoms and working memory ability was found to become worse over time. Study two utilized a latent growth model of the trajectory of depressive symptom development following the loss of a spouse. Results indicated that the starting point of initial depressive symptom endorsement was
significantly related to working memory ability. Working memory also moderated the relationship between depressive symptom endorsement and time, where individuals with better working memory tended to report lower depressive symptoms and demonstrated a lesser increase in depressive symptoms. Study three utilized a multilevel model that demonstrated depression increases over time and with age. Regardless of time, better sleep quality and better working memory both result in lower depressive symptom endorsement, and there were associations between lower depressive symptom endorsement and both better sleep quality and better working memory.

Conclusions: Findings strongly support working memory, sleep quality, and spousal support as emotion regulation resources within the context of the SOC-ER model. Future research should continue to examine these and similar interrelated factors such as inhibitory control, processing speed, and vascular burden longitudinally to provide further understanding of changes in emotion regulation processing among older adults.
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CHAPTER ONE: STUDY 1 INTRODUCTION

Mood and emotions are complex and dimensional short-term responses to assist with fundamental goal attainment (Ekman, 1999). Every situation encountered that is attended to is appraised and elicits an evaluative response based on current goals, such as a desired emotion or mood. These responses are characterized, physiologically, dimensionally through changes in expressive behavior, and through subjective experience (Gross & Thompson, 2007). The dimensional nature of these reactions means that not all combinations are necessarily adaptive, as the strength, duration, or situation in which the response occurs may not be appropriate (Gross & Thompson, 2007). Aging is typically accompanied by loss and health decline, and depressive symptoms (Chui et al., 2015) are of particular concern. Many older adults live happy and satisfactory lives despite these changes; however, the prevalence rate for depression in older Americans is 13.6% (Centers for Medicare and Medicaid Services, 2014), which is more than double that of the general population (Hunter & Tice, 2016). High rates of depression and ineffective emotion regulation skills among older adults have many contributing factors, one of which is poor working memory (Coifman et al., 2019; Nieto et al., 2019; Schmeichel & Tang, 2015). In addition, some studies have demonstrated the inverse effect of higher rates of depression resulting in poor working memory (Christopher & MacDonald, 2005; Chui et al., 2015). The goal of this study is the examination of bidirectional effects between working memory and mood in a longitudinal, demographically representative sample of older adults living in the United States.

Regulation of Mood

Although the regulation of emotion was examined as early as the 1950’s, many incorrect
assumptions were accepted without empirical support until work by Gross (1998) created a foundation for contemporary research into emotion. He suggested that emotions are managed through a 5-step process that begins with situation selection or determining whether to choose a situation based on the likelihood of eliciting a particular emotion. This progresses to situation modification, which is altering a situation to try to elicit a particular emotion. Attentional deployment follows by either attending to the situation or shifting focus elsewhere. Cognitive change can occur next, where the meaning of the situation can be reinterpreted to modify the associated emotion. The final step is response modulation, which is a direct and intentional change to expressive behaviors, physiology, and subjective experiences related to the situation (Gross, 1998; Gross & Thompson, 2007; Urry & Gross, 2010).

Though the 5-step process of emotion regulation can be applied across the lifespan, there is limited research examining older adults as most existing research has focused on young adults. Due to this, the unique interpersonal and physiological differences that characterize older adults require further examination. To date, the extant research that has compared young and older adults has demonstrated several differences between the age groups. For example, based on subjective reporting, older adults believe they are better at controlling their emotions as compared to younger adults (Gross et al., 1997). Similar perceptions have continued to be demonstrated cross-sectionally, as self-reports from older adults indicate lower levels of negative affect and higher levels of positive affect than younger adults (Charles et al., 2015; Stawski et al., 2008). Longitudinal studies have also demonstrated improvement in subjective well-being (Cacioppo et al., 2008), and age-related decline in both general negative affect (Charles et al., 2001) and negative affect related to argument avoidance (Benson et al., 2019; Charles et al., 2009).
It has been suggested that the perceived experiences of emotions may be related to improved situational selectivity (Urry & Gross, 2010). As adults age, there is a tendency to consolidate social networks with fewer but closer and happier relationships (Luong et al., 2011; Sims et al., 2015). Furthermore, a recent study along with a meta-analysis demonstrated that older adults also employ attentional selectivity regarding their focus on incoming information, attending more to positive than negative information (Martins et al., 2018; Reed et al., 2014). When attending to negative stimuli such as pain experienced by others, older adults tend to experience more distress than young adults (Bailey et al., 2018). This in conjunction with the substantial benefit gained by shifting from negative incoming stimuli to a positive autobiographical memory (Phillips et al., 2008) suggests that applying selectivity to emotion regulation may provide a method of optimizing mood and compensating for negative experiences among older adults.

**Selection, Optimization, and Compensation with Emotion Regulation Model (SOC-ER)**

In 1990, Baltes and Baltes proposed a theoretical framework to delineate successful living. Termed the model of selection, optimization, and compensation, they posited that there are three aspects involved in the process: 1) determining goals that are realistic based upon the parameters of their own capabilities and limitations (selection); designate time, practice, and energy to achieving selected goals (optimization); and increase efforts, develop adjustments, or obtain help to compensate for losses (compensation; Baltes & Baltes, 1990).

There is a broad range of applications for the initial framework of the model proposed, with one of them being emotion regulation. Conceptualized by Urry and Gross (2010), they postulated that due to age-related changes, older adults must compensate for escalating age-
related loss of emotion regulation resources. This may be achieved through selection and optimization of alternate approaches to emotional regulation, particularly approaches that are more likely to succeed due to newly obtained resources or more commonly, resources (i.e., cognition, acquired skills, or social network optimization) that may persist despite age-related changes. Resources can be thought of as either internal abilities or external factors that facilitate emotion regulation. For example, as Opitz et al. (2012) described, working memory can be considered as an internal resource that allows for control and manipulation of the contents within its storage. It also assists with identification of positive and negative information and plays a role in its reappraisal. These aspects of working memory likely aide in the process of altering emotions to align with current goals. To consider an external resource, such as spousal support, may involve attributes such as the ability to redirect attention toward more desirable aspects of situations or facilitate its reappraisal, or even provide access to alternative situations more in line with one’s own goals. Although there has not been much research to date on these emotion regulation resources among older adults, Opitz et al. (2012) has described a conceptual framework from which the current study aims to begin.

**Working Memory**

To date, the studies that have been conducted examining the resources involved in cognitive regulation of depression have focused primarily on different aspects of executive functioning, such as working memory. Working memory has been described as the process by which information is temporarily stored and maintained while engaging in complex cognitive processing (Baddeley, 2002). As such, it has been identified as a potential resource necessary in the process of regulating depression. Initial studies that examined working memory capacity
demonstrated that those with better working memory were able to evaluate emotional stimuli more objectively than those with worse working memory (Schmeichel et al., 2008). Follow up studies also reported that individuals presented with negative feedback engaged in more self-enhancement (positively reaffirming themselves) when their working memory capacity was better (Schmeichel & Demaree, 2010), as well as experiencing more success when using emotion regulation strategies such as expressive suppression, cognitive reappraisal, and coping with daily stressors (Schmeichel & Tang, 2015). Among older adults in a post-operative setting, a recent study showed that working memory training improved performance on similar working memory tasks but also decreased in depressive symptom endorsement compared to those who did not receive training (Carbone et al., 2019).

Cross-sectional studies suggest that working memory declines at a fairly even rate across the adult life span and is lowest in older age (Borella et al., 2008; Heinzel et al., 2017; Swanson, 2017). These changes have also been examined longitudinally using diffusion tensor imaging, with results indicating that normal age-related deterioration of prefrontal white matter is associated with worsening working memory performance (Charlton et al., 2010). These findings suggest that good working memory ability has beneficial implications regarding the regulation of depression, though age-related changes may diminish successful regulation.

While the previously discussed findings indicate the directional effect of working memory predicting depressive symptoms, there is also a great deal of support for the inverse relationship. Depressed older adults have been shown to perform worse than nondepressed participants on working memory tasks (Dumas & Newhouse, 2015), with a similar pattern of findings of specific working memory and central executive function impairment among individuals with MDD (Christopher & MacDonald, 2005; Dumas & Newhouse, 2015; Lopez-
Higes et al., 2018; Rose & Ebmeier, 2006). Given the extent of mixed findings, the directionality of these effects remains unclear and requires further elucidation.

**Primary Goals and Hypotheses**

The extant literature discussed in this paper demonstrated initial cross-sectional support for the role of cognitive ability, particularly working memory, as a crucial emotion regulation resource for depression. It is important to understand how this process occurs when emotion regulation resources are burdened, such as with age-related cognitive decline. The present study is an attempt to elucidate the relational trajectory of depression and working memory by utilizing longitudinal data and a three-faceted hypothesis. Specifically, the longitudinal inter-relationships between working memory and depression will be examined across five waves spanning 8 years of later-life (youngest first wave age 65 years). The temporal sequence between depressive symptoms and the manifestation of working memory performance among aging older adults will be examined using a dual change growth model. This model tests the hypotheses that (1) working memory will predict depressive symptoms over time, that (2) depressive symptoms in the initial wave will positively predict future depressive symptoms, and given the conflicting findings across the literature, the alternative theory that (3) depressive symptoms will predict working memory, is also examined by this model (see examined model in *Figure 1*). Based on past work, biological sex, education, race, and age were selected *a priori* as control variables.
CHAPTER TWO: STUDY 1 METHOD

Participants
Data from the Health and Retirement Study (HRS) was utilized. This longitudinal dataset is sponsored by the National Institute on Aging and collected through the University of Michigan. Participants provided informed consent in accordance with the procedures of the University of Michigan Institutional Review Board, and the present study was approved by the University of Central Florida Institutional Review Board. Data have been collected every two years since 1992 and consists of randomly selected participants, with additional information on HRS design and collection methods found in published reports (Hauser & Willis, 2004; Weir et al., 2016). This study utilized waves 8 (2006) through 12 (2014), including 21,375 participants of the total HRS database’s 42,053 participants who were age 65 and older by the selected baseline wave (see Figure 2).

Measures

Demographic variables
Age, biological sex, and race were self-reported by the participant. Race was recoded to White and non-White to protect the identity of participants, as specifying race (i.e., Native American and Pacific Islander) and age of some older adult participants would pose greater than necessary risk of identification. Education was assessed as self-reported years of formal schooling completed.

Working Memory
Working memory was represented using the Serial 7’s test, which requires participants to subtract seven from 100 and each subsequent sum (i.e., 100-7, 93-7, etc.) for a possible score. References and measure descriptions for this measure can be accessed online (Hauser & Willis, 2004; Weir et al., 2016).

Depression

Depression was measured using a shortened version of the Center for Epidemiological Studies Depression (CES-D) measure (Radloff, 1977). The shortened CES-D is a dichotomized (yes/no) eight question measure with a possible score range from zero to eight. All positive items were reverse scored. The original measure has demonstrated both high internal consistency (Cronbach’s alpha .85 to .90), and validity (Radloff & Teri, 1986) among older adults, though the shortened CES-D’s internal consistency was mildly lower (Cronbach’s alpha .82). For the purposes of this study, CES-D was treated as continuous despite having a cutoff score that indicates probable depression (Koenig & Blazer, 1992).

Statistical Methods

Examination of primary hypotheses required considerable data preparation. The proposed hypotheses were analyzed using a latent growth curve model. Because missing data in longitudinal modeling is problematic and mortality-based attrition occurred within the study population, full information maximum likelihood estimation (FIML) was utilized. This approach allowed for the estimation of model parameters despite missing data (McArdle & Hamagami, 1992), which reduced the underrepresentation of such individuals. To improve parameter estimates, the Robust Maximum Likelihood (MLR) estimator was used.

Data were prepared using SPSS v27 (IBM Corp, 2020), and the Mplus software program (Muthén & Muthén, 2019) was employed for all analyses. Hypotheses one, two, and three,
relating working memory to depressive symptoms over multiple time points was examined using the model displayed in Figure 1. Planned analyses employed Level 1 and Level 2 latent growth models. The first unconditional latent growth model (Raykov & Marcoulides, 2008) was estimated by modeling the association between depression and working memory and demonstrating their change over time without predictors. Next, a conditional Level 2 model examined change in endorsement of depressive symptoms over time by working memory ability, as well as the inverse relationship, while including predictor variables such as biological sex (dichotomous), education (continuous), race (White versus non-White; and Hispanic versus non-Hispanic; dichotomous). This model included parameters reflecting intercept and linear slope terms for both depressive symptoms and working memory. All variables except CES-D score were mean centered.

For all models, three fit indices are examined to determine model fit: chi-square test of significance, the comparative fit index (CFI), root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). A model is shows acceptable fit when the CFI is larger than .90, RMSEA is smaller than .08, and the SRMR is smaller than .08 (Browne & Cudeck, 1992). The chi-square test of significance is reported but not used as a measure of model fit, because it is highly sensitive to sample size.
CHAPTER THREE: STUDY 1 RESULTS

Demographics and Cognitive Performance

The total sample for hypotheses 1-3 consisted of 21,375 participants, which had an average age of 86.29 ($SD = 13.53$), was largely female (55.47%), and predominately White/Caucasian (77.09%) and non-Hispanic (89.70%). The sample was of average education ($M = 11.96$, $SD = 3.49$ years). The sample had an average CES-D score that fell within the minimal range ($M = 1.23$, $SD = 1.78$) and an average Serial 7’s score of 3.51 ($SD = 2.92$) at their wave used as baseline. Full participant characteristics can be found in Table 1.

Depressive Symptom Development

Level 1

Overall, results suggest that the hypothesized model fit the data very well: $\chi^2 (41) = 173.189$, $p<.001$ RMSEA=0.012 [0.010 0.014]; CFI=0.997, SRMR=0.011. The model indicated significant associations between the slope and intercept of depressive symptoms ($r(21,373)=-0.081$, $p<.001$), the intercept of working memory with the intercept of depressive symptoms ($r(21,373)=-0.725$, $p<.001$) and the slope of depressive symptoms ($r(21,373)= 0.026$, $p<.001$), between the slope of working memory and the slope of depressive symptoms ($r(21,373)= -0.009$, $p<.001$), but not between the slope of working memory and the intercept of working memory or the intercept of depressive symptoms. Across the five waves, these associations accounted for between 58.1% to 64.1% of the variance in depressive symptom endorsement and between 66.1% to 71.2% of the variance in working memory.

Level 2
Overall, results indicate that the hypothesized model fit the data very well: $\chi^2(67) = 184.863, p<.001$ RMSEA=0.009 [0.008 0.011]; CFI=0.998, SRMR=0.008. Specific model results showed a significant direct effect of the intercept of depression on the slope of depression ($b=-0.031, SE=0.006 p<.001$) but not of the slope or intercept of working memory. Similarly, there was a significant direct effect of the intercept of working memory on the slope of working memory ($b=-0.011, SE=0.005 p<.05$) but not the slope or intercept of depression. Together, these findings indicate that the baseline of both depressive symptoms and working memory have a negative effect on the trajectory of their respective slopes longitudinally.

An examination of the direct effects of the aforementioned exogenous variables revealed that baseline depressive symptom endorsement and baseline working memory performance were significantly associated with biological sex, education, race (White versus non-White; and Hispanic versus non-Hispanic (see Table 2). Age was the only significant direct effect on the slope of depression, while there were significant direct effects of education, biological sex, and age on the slope of working memory. With the addition of these control variables into the model, there was a negligible change in variance accounted for across the five waves. $R^2$ for depressive symptom endorsement ranged from 58.0% to 64.2%, while it ranged between 66.0% to 71.9% of the variance in working memory.
Primary findings from this study partially supported initial hypotheses and are generally consistent with extant literature. While non-directional relationships between depression and working memory cross-sectionally and over time were supported, directional effects were not. Although the model fit well, hypothesis 1 that working memory would negatively predict depressive symptom endorsement over time was not supported. Hypothesis 2 that past depressive symptom endorsement would predict future symptom endorsement was supported, though of note, higher depression scores at baseline were associated with a plateau or modest decrease over time. Hypothesis 3, which tested the inverse of hypothesis 1 – that depressive symptom endorsement was negatively associated with working memory ability - also was not supported.

Given the inconclusive evidence regarding the temporal precedence between working memory and depression, the initial model that instead examined depression and working memory changing with one another was considered. This approach showed significant negative associations between the slope of working memory and slope of depression as well as the intercept of depression with both the slope and intercept of working memory, suggesting an association that could not be modeled using directional effects when controlling for demographic factors. The relationship between depression and working memory has not been researched extensively among older adults, and those that have examined it produced contradictory results in terms of directionality (Panza et al., 2009; van den Kommer et al., 2013; Wilson et al., 2014; Xingjia Cui et al., 2007). More recently, a longitudinal study examining a large cohort of older adults demonstrated similar findings of a bidirectional relationship between depression and working memory (Desai et al., 2020). It may be possible that the relationship between working memory and depression may be better explained by other variables beyond the scope of this
study, such as neurovascular changes represented by white matter integrity or age-related cortical shrinkage, the impact of accumulated medical burden at the end of life, or grief and loss (Fries et al., 2011).

The findings from this study provide additional support to previous studies for a variety of demographic factors, especially age (Lyness et al., 2009), as particularly influential of both depressive symptom endorsement and working memory performance at baseline. As the aging process is accompanied by a myriad of changes that can impact the overall success of emotion regulation, it is crucial to understand the available resources that can be utilized to regulate depressive symptoms as they develop within the context of natural age-related changes. Working memory in particular is an emotion regulation resource that is crucial from the SOC-ER model standpoint. To effectively update information and reappraise situations requires the use of working memory, and studies have demonstrated that this is a more difficult endeavor to engage in for those who have MDD and working memory deficits (Harvey et al., 2005; Snyder, 2013). Relative working memory impairment may handicap social goal setting, marshaling effort for achievement of selected goals, and reappraisal or readjustment of efforts, resulting in higher probability of poor emotion regulation (Opitz, 2013). As such, the current study demonstrated an important aspect of the selection, optimization, and compensation for emotion regulation framework that built on past work and provided direction for future research examining depression within the context of working memory (Opitz et al., 2012; Opitz et al., 2014).

Practical implications of these results support the need for treatment tailored particularly for older adults. Research has shown that older adults with executive deficits exhibit worse response to both antidepressant medication regimens (Mackin & Arean, 2005; Sneed et al., 2010) and psychotherapy compared to depressed older adults with normal executive performance.
(Beaudreau et al., 2015). Problem solving therapy is also an effective treatment for depression with dysexecutive features, and it seeks to reframe maladaptive thinking towards goal identification, the development of action plans to achieve the identified goals, and a process to evaluate progress (Alexopoulos et al., 2008; Alexopoulos et al., 2011). Another benefit these findings provide is a useful framework for clinicians who are performing neuropsychological or memory disorder evaluations. By understanding the nature of the relationship between working memory and depression, clinicians can better anticipate testing results, patient needs, and likely trajectories of decline based on testing results and mental health status. Furthermore, it suggests limitations to neuropsychological data validity, particularly among older adults with depression.

**Limitations**

A potential limitation to the current study was the conceptualization of working memory. In the current study, working memory was represented by Serial 7’s total correct responses. Although this task has generally been described as a working memory task, it may not be as sensitive as other working memory tasks or a composite variable of multiple working memory tasks. This may be an important distinction to make when examining working memory in depression, as Friedman and Miyake (2004) have demonstrated that the ability to stop unwanted intrusive thoughts relies significantly on interference control rather than other aspects of executive function such as working memory.

In addition, the SOC-ER model has generally been used to demonstrate a framework for emotion regulation overall, while the current study sought to apply it directly to regulation of depressive symptoms within the context of working memory. Given that this framework posits emotion regulation requires the utilization of appropriate resources, along with this study’s
findings that the relationship between depression and working memory is more symbiotic in nature, including working memory in the SOC-ER model is imperative to understand the mechanisms underlying the regulation of depression in older adults.
CHAPTER FIVE: STUDY 2 INTRODUCTION

Selection, Optimization, and Compensation with Emotion Regulation Model (SOC-ER)

The incidence rate of spousal loss among older adults is approximately 8.1% over a 30-month period (Williams et al., 2007). In addition, approximately 40% of women and 13% of men over the age of 65 are widowed and often experience emotional, physical, cognitive, and social decline as a result. Grief is a typical response to loss. Grief slowly diminishes over time, though some develop complex bereavement and other mental health disorders (Sasson & Umberson, 2013; Szabó et al., 2019). As such, it is important to identify and understand the characteristics of those who experience additional difficulty after this type of loss. The theoretical framework termed the model of selection, optimization, and compensation was developed to outline successful living. This framework posited that there are three aspects involved in the process: 1) determining goals that are realistic based upon the parameters of their own capabilities and limitations (selection); designate time, practice, and energy to achieving selected goals (optimization); and increase efforts, develop adjustments, or obtain help to compensate for losses (compensation; Baltes & Baltes, 1990). Urry and Gross (2010) furthered this theory by applying it to age-related changes, specifically noting that older adults must compensate for escalating age-related loss of emotion regulation resources. The goal of this study is to examine, in a large, longitudinal, demographically representative sample of older Americans, how working memory capacity impacts the expression of depression symptoms after spousal loss.

Spousal support has since been identified as a vital emotion regulation strategy, particularly because social networks tend to shrink in later life as a result of socioemotional selectivity, mortality, and incapacity (d'Epinay et al., 2010; Naef et al., 2013; Spahni et al., 2015). For example, an adaptive response following the loss of a partner typically results in the
appropriate response of uncomplicated bereavement-related grief. Although grief entails some symptoms of depression, the strength, duration, and situation of the symptoms distinguish it from clinically diagnosable depression. These symptoms have been shown to persist on average for approximately three years (Robinson-Whelen et al., 2001). However, if the symptoms worsen in intensity or the duration persists without improvement, which occurs in around 10% of bereaved people, there has not been a transition from acute grief to integrated grief and the potentially adaptive response of grief shifts towards a maladaptive response on the continuum (Zisook & Shear, 2009).

The death of a spouse and the subsequent process of bereavement presents a tangible challenge to affect regulation in later life. Results of this process are highly variable between older adults. Acute grief is inherently stressful at any age, and that impact may be exaggerated by the developmentally typical social network consolidation (Blanchard-Fields et al., 2004; Nolen-Hoeksema & Aldao, 2011; Wrzus et al., 2013). Successful bereavement is an affectively and cognitively demanding process, but one that offers a gradual reduction in distress related to the loss (Jordan & Litz, 2014). It follows, then, that emotion regulation resource availability likely predicts successfulness of bereavement, as was suggested in a meta-analysis by Lundorff et al. (2017). Results of the meta-analysis showed that older adults with better general health (i.e., nutrition and sleep) and good social support disengaged less from the world and were better able to redirect their attention from the loss. The alternative, which is prolonged, unresolved grief, also known as complex bereavement, has been shown to often precipitates late-life depression (Zisook & Shear, 2009). For this reason, the common event of spousal bereavement among older adults who differ with respect to working memory capacity may be considered as a natural experiment in affect regulation.
Primary Goal and Hypothesis

Given the extent to which social pruning occurs among older adults along with the increased reliance on a spouse as the primary component in their social network, it is important to consider this dynamic from the SOC-ER framework. The spouse of an older adult is a key emotion regulation resource, and as such, it is necessary to understand how well older adults select and optimize regulation of depressive symptoms when this resource is no longer available. Given the theorized importance of working memory to coping and successful grieving and the known age-related decline in working memory, it follows that among older adults working memory may predict the expression of depressive symptoms following the loss of a spouse. This study aims to address the gap in the literature is how these variables function longitudinally. To represent this goal, the conceptual model represented by Figure 3 was proposed.

The primary goal of this study was to examine the effect of working memory on depression following a significant negative life event (spousal loss). Specifically, it is hypothesized that working memory (measured using serial 7’s) will negatively predict depressive symptom endorsement following the loss of a spouse.
CHAPTER SIX: STUDY 2 METHOD

Participants

Data from the Health and Retirement Study (HRS) was utilized. This longitudinal dataset is sponsored by the National Institute on Aging and collected through the University of Michigan. Participants provided informed consent in accordance with the procedures of the University of Michigan Institutional Review Board, and the present study was approved by the University of Central Florida Institutional Review Board. Data have been collected every two years since 1992 and consists of randomly selected participants, with additional information on HRS design and collection methods found in published reports (Hauser & Willis, 2004; Weir et al., 2016). This study utilized waves 2 (1994) through 12 (2014), including 3,599 participants of the total HRS database’s 42,053 participants who were age 65 and older and experienced the loss of a spouse during the course of data collection (see Figure 4).

Measures

Demographic variables

Age, biological sex, and race were self-reported by the participant. Race was recoded to White and non-White to protect the identity of participants, as specifying race (i.e., Native American and Pacific Islander) and age of some older adult participants would pose greater than necessary risk of identification. Education was assessed as self-reported years of formal schooling completed. All variables that were included in analyses were mean centered with the exception of CES-D.

Working Memory
Working memory will be represented using the Serial 7’s test. References and measure descriptions for this measure can be accessed online (Weir et al., 2016).

**Depression**

Depression was measured using a shortened version of the Center for Epidemiological Studies Depression (CES-D) measure (Radloff, 1977). The shortened CES-D is a dichotomized (yes/no) eight question measure with a possible score range from zero to eight. All positive items were reverse scored. The original measure has demonstrated both high internal consistency (Cronbach’s alpha .85 to .90), and validity (Radloff & Teri, 1986) among older adults, though the shortened CES-D’s internal consistency was slightly lower (Cronbach’s alpha .82). For the purposes of this study, CES-D was treated as continuous despite having a cutoff score that indicates probable depression.

**Loss**

For the mortality status of a spouse/partner, responses to the following questions from the HRS database will be examined: “previous wave spouse/partner die during study?”, “divorce/widow since previous wave?”, and “number of times widowed?” For the purpose of analyses, the wave during which the loss occurred will be considered as the participant’s Baseline (Loss) Wave, with subsequent waves being included to the extent to which there is appropriate covariance coverage.

**Statistical Methods**

The proposed hypotheses were analyzed using a structural equation model, specifically, a latent growth curve analysis. Because missing data in longitudinal modeling is problematic and there was mortality-based attrition within the study population, full information maximum likelihood estimation (FIML) was utilized. This approach allowed for the estimation of model
parameters despite missing data (McArdle & Hamagami, 1992), which reduced the underrepresentation of such individuals.

Robust Maximum Likelihood (MLR) estimator was used to improve parameter estimates. The *Mplus* software program (Muthén & Muthén, 2019) was employed for all analyses. The hypothesis examined the trajectory of depressive symptoms over time, following the loss of a spouse, within the context of working memory ability as displayed in *Figure 3*. This hypothesis was examined using a latent growth analysis in which retained participants lost a spouse to death. Data were stacked such that the effective baseline for this analysis was the wave during which spousal loss occurred. The intercept and slope of the wave of the reported spousal mortality (hereafter referred to as, “loss wave”) and subsequent “post-loss” waves were examined in context of the pre-loss wave’s working memory (serial 7’s) score. To demonstrate the moderating effect of working memory on depressive symptom endorsement over time, the model was run three times and simple slopes were examined with working memory fixed at the mean, one standard deviation above, and one standard deviation below the mean. The proposed analyses controlled for biological sex, education, race (White versus non-White; Hispanic versus non-Hispanic).

For all models, three fit indices are examined to determine model fit: chi-square test of significance, the comparative fit index (CFI), root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). A model is shows acceptable fit when the CFI is larger than .90, RMSEA is smaller than .08, and the SRMR is smaller than .08 (Browne & Cudeck, 1992). The chi-square test of significance is reported but not used as a measure of model fit, because it is highly sensitive to sample size.
CHAPTER SEVEN: STUDY 2 RESULTS

Demographics and Cognitive Performance

The total sample included 3,599 participants, all of whom experienced the loss of a spouse over the course of data collection. This sample was comprised of participants with an average age 78.04 ($SD = 7.32$) at the time of their spouse’s death. Participants were largely female (69.10%), White/Caucasian (82.30%), non-Hispanic (92.37%), and completed an average of 11.61 ($SD = 3.42$) years of education. Participants had an average serial 7’s score of 3.29 ($SD = 1.70$) the wave prior to the loss. At the loss wave, the average CES-D score was 2.53 ($SD = 2.26$). Full demographic information can be found in Table 3.

Depressive Symptoms Post-Loss

Planned analyses included level 1 and level 2 latent growth models. The level 1 model was run to establish a framework for examining the intercept and linear slope of change in depressive symptom endorsement over time without predictor variables. Following this model was the conditional level two moderated growth analysis examining the intercept, linear slope, and quadratic slope of change in depressive symptom endorsement over time. Predictor variables included biological sex, education, race (White versus non-White; and Hispanic versus non-Hispanic), while the moderating effect of working memory was demonstrated by examining its effects while it was fixed at the mean, one standard above, and one standard deviation below the mean.

Level 1

The unconditional growth model was fitted to the data including a maximum of eight repeated assessments of depressive symptom endorsement beginning at the loss wave. Overall,
results suggest that the hypothesized level 1 model fit the data well: $\chi^2(30) = 50.389, p = .011$ RMSEA=0.013 [0.006 0.020]; CFI=0.992, SRMR=0.028. Based on previous research that demonstrated a nonlinear change in depressive symptoms among older adults (Paulson et al., 2018; Teachman, 2006), this model was run again including a quadratic term. This revised model resulted in a better overall model fit $\chi^2(26) = 32.353, p = .18$ RMSEA=0.008 [0.000 0.016]; CFI=0.998, SRMR=0.023, indicating a nonlinear change over time. As such, the quadratic term was retained in the level 2 model.

Level 2

Overall, results suggest that the hypothesized level 2 model fit the data very well: $\chi^2(56) = 61.323, p = .29$ RMSEA=0.005 [0.000 0.012]; CFI=0.998, SRMR=0.028. The model indicated (a) significant linear ($b = -0.093, SE = 0.042, p = .027$), and quadratic ($b = 0.016, SE = 0.006, p = .011$) effects at the mean of working memory; (b) significant linear ($b = -0.127, SE = 0.052, p = .015$) and quadratic effects ($b = 0.024, SE = 0.008, p = .003$) at one standard deviation below the mean of working memory; and (c) nonsignificant linear ($b = -0.058, SE = 0.047, p = .212$) and quadratic ($b = 0.008, SE = 0.007, p = .262$) effects at one standard deviation above the mean of working memory (see Figure 5). There was a significant main effect of working memory ($b = -0.086, SE = 0.023, p < .001$), non-Hispanic ($b = 0.429, SE = .164, p < .001$), and years of education ($b = 0.064, SE = .013, p < .001$) on the intercept of depressive symptoms, but not the slope or quadratic. There was, however, a significant main effect of the age of loss on the slope of depressive symptoms ($b = -0.008, SE = .004, p = .032$). There was also a significant amount of variance accounted for at the loss wave ($r^2 = 0.52, p < .001$), which steadily increased over time reaching $r^2 = 0.74, p < .001$ seven waves or 14 years post-loss. The intercept of CES-D also
accounted for a significant amount of variance \( (r^2 = .05, \ p < .001) \), but not the slope \( (r^2 = .04, \ p = .092) \) or the quadratic \( (r^2 = .05, \ p = .187) \).
CHAPTER EIGHT: STUDY 2 DISCUSSION

Primary findings from this study provide partial support of the proposed hypothesis. The initial increase in depressive symptom endorsement following the loss of a spouse does decline with time. And although there was not a direct effect of working memory on either the slope nor the quadratic, findings showed that the intercept, or starting point of initial depressive symptom endorsement is significantly related to working memory ability. These findings indicated that working memory moderated the relationship between depressive symptom endorsement and time, where individuals with better working memory tended to report lower depressive symptoms but also demonstrated a lesser increase in depressive symptoms later in life. Further, the pattern of results provides additional evidence for working memory as a protective factor against depressive symptom endorsement in later life.

Although there is limited extent literature on this subject currently, recent longitudinal findings demonstrated that loss of spouse was also related to cognitive decline, specifically with a relationship between time since spousal loss and cognitive decline (Shin et al., 2018). When spousal loss occurs in concurrently with an age-related reduction in the efficiency of working memory, the combination of lost emotion regulation resources leaves older adults at risk of developing additional depressive symptoms. However, social support, such as having at least one living sibling and higher education (Shin et al., 2018) both appear to serve as protective factors against cognitive decline potentially by providing alternative forms of the lost emotion regulation resources.

The aging process is accompanied by a myriad of health changes that can impact the overall success of emotion regulation. Though there are many possible resources that can be utilized for regulating depression, the current study demonstrated another important aspect of the
selection, optimization, and compensation for emotion regulation framework that builds on past work (Opitz et al., 2012; Opitz et al., 2014). As aging is accompanied by a reduction in the efficiency of cognitive functioning, further information is needed to elucidate how this affects emotion regulation. By relating cognitive functioning and depressive symptoms through the extension of previous findings longitudinally, this will provide a better understanding of individual trajectories to emotion dysregulation, particularly those related to depression.

Examining the results longitudinally helped to identify time-related resource changes, which informed treatment identification. Furthermore, understanding how various adaptive emotion regulation resources (i.e., spousal support and working memory) are among older adults following a period of loss (i.e., the death of spouse) provides insight into the transition from grief to bereavement and assists with informing treatment as well. In other words, these results helped to stratify the risk of complicated bereavement following a loss worsening based on working memory ability and implement treatment in a more time-efficient manner.

In terms of practical application of these findings, this study highlights the importance of developing intervention programs tailored toward supporting widows/widowers as well as recommending the involvement of family as an alternative source of support. These findings are also helpful for informing clinicians of appropriate treatment selection, as treatments such as cognitive training have been shown to be more effective with older adults who have better inhibition efficiency and working memory ability (Lopez-Higes et al., 2018). Overall, this research provided a more complete model of aging, particularly within the context of age-related loss. The relationship between working memory and depression, and sleep and depression, as well as insight as to how these change over time.
Limitations

A potential limitation to the current study was again the conceptualization of working memory. In the current study, working memory was represented by Serial 7’s total correct responses. Although this task has generally been described as a working memory task, it may not be as sensitive as other working memory tasks or a composite variable of multiple working memory tasks. Another limitation was that following the loss of a spouse, the next data collected from a given participant did not occur for approximately two years. Although beyond the scope of the current study due to the design of data collection, it is possible that the process of grief and bereavement primarily occurs within the two years following the loss and is more affected by working memory and social support during that timeframe. Furthermore, the current study was unable to model the full extent of the impact of race, culture, and biological sex, all of which contribute to outcomes following spousal loss. These variables are particularly important to consider in future research, especially in regard to biological sex differences, as older adult males tend to fare worse both emotionally and in terms of physical health following the loss of their spouses (Lee & DeMaris, 2007).

In conclusion, the SOC-ER model has generally been used to demonstrate a framework for emotion regulation overall. The current study sought to apply this model directly to regulation of depressive symptoms within the context of both working memory and social support. To this author’s knowledge, very few studies (Opitz, 2013; Opitz et al., 2014), have considered working memory ability among older adults as an emotion regulation resource, let alone within the context the loss of another crucial emotion regulation resource such as spousal support. Given the extent to which spousal support and working memory function as emotion
regulation resources, the SOC-ER model may be imperative to understand the mechanisms underlying the regulation of depression in older adults.
CHAPTER NINE: STUDY 3 INTRODUCTION

Sleep

Sleep is a complex, multifaceted behavior that is related to a wide variety of behavioral and physiological outcomes including mood (de Almondes et al., 2016; Franzen & Buysse, 2008; Sivertsen et al., 2012). There are a variety of common variables that can be measured to account for the quality of sleep, such as total sleep time (total duration of sleep during period of time in bed), sleep onset latency (time from lights-off to the first epoch of sleep), wake after sleep onset (total duration of wake time after sleep onset), sleep efficiency (total sleep time divided by total time in bed), and most commonly, self-reported quality of sleep (Baillet et al., 2016; Cook et al., 2017; Diaz et al., 2015; Kang et al., 2017). It is recommended for older adults to sleep between 7 and 8 hours a night, though considerable variability around those guidelines is common (Buxton & Marcelli, 2010). Sleep disruption and increased variability in sleep quality commonly occur with age (Ohayon et al., 2004). While approximately 40%-70% of older adults experience sleep problems, it is estimated that approximately 50% are undiagnosed (Miner & Kryger, 2017). As older adults age from young-old, to old-old, to oldest-old, research has also shown an increased likelihood of sleeping less than six hours per night with oldest-old experiencing the worst sleep quality (Hägg et al., 2014). As such, the goal of this study is to demonstrate the role of sleep quality as an emotion regulation resource for depression.

The relationship between sleep and mood is likely to be bidirectional, with studies demonstrating that worse sleep leads to depressive symptoms (Cheng et al., 2018; Franzen & Buysse, 2008; Sivertsen et al., 2012). By contrast, abundant findings have characterized the inverse, with depressed mood resulting from poor sleep (Ancoli-Israel, 2004; Dinges et al., 1997; Lopresti et al., 2013). However, a meta-analytic review of longitudinal research found that poor
Sleep quality doubles the likelihood of prospectively developing major depression (Baglioni et al., 2011). High rates of depression and ineffective emotion regulation skills among older adults have many contributing factors, and based on literature discussed herein, it follows that poor sleep quality has a role in these difficulties (Cole & Dendukuri, 2003; Foley et al., 2004; Robert D Nebes et al., 2009). What these findings suggest given the way in which sleep functions as a regulatory resource, is that sleep deserves consideration from the theoretical framework termed the model of selection, optimization, and compensation (SOC-ER; Baltes & Baltes, 1990). This framework posited that there are three aspects involved in the process of successful living: 1) determining goals that are realistic based upon the parameters of their own capabilities and limitations (selection); designate time, practice, and energy to achieving selected goals (optimization); and increase efforts, develop adjustments, or obtain help to compensate for losses (compensation; Baltes & Baltes, 1990).

Poor sleep has also been associated with cognitive decline in older adults (Naismith et al., 2009). The association between poor sleep and cognitive functioning among older adults has been well documented, with research indicating that there may be an increased susceptibility to the effects of sleep loss on cognition (Bruce & Aloia, 2006; Dzierzewski et al., 2018). Age-related changes in the circadian rhythm, typically from a later onset to an earlier onset, can also affect both sleep quality and cognition. Failure to adapt to these age-related circadian rhythm changes by changing the sleep schedule leads to fewer hours asleep; late sleep onset, which may have been more adaptive in early or mid-life, becomes paired with an earlier natural waking due to the cycle shift (Ancoli-Israel, 2004). Further, Oosterman et al. (2009) found that disruption of the sleep-wake cycle is associated with decline on a number of cognitive domains, including executive functioning, processing speed, and memory. This is of note, as Schmidt et al. (2007)
found effects of circadian and time-of-day on cognition, and eveningness, which is the characteristic of being more active during the evening, has been shown to correlate positively with cognitive ability (Preckel et al., 2011). This suggests that the shifting circadian rhythm likely contributes to the deterioration of cognitive performance among older adults.

During sleep, important physiological functions that have implications on the brain such as metabolite elimination (Xie et al., 2013) and tissue regeneration (Adam & Oswald, 1977) also occur. Without sleep, potentially neurotoxic waste central to neurodegenerative disease pathogenesis such as Amyloid-β continues to accumulate during waking hours and remains in the central nervous system (Cirrito et al., 2005; Xie et al., 2013). Poor sleep quality and duration is also taxing to the vascular system, as studies have shown a U-shaped relationship where too few (≤ 6) and too many (≥ 9) hours of sleep is strongly associated with hypertension (Buxton & Marcelli, 2010; Guo et al., 2013), cardiovascular disease (Ayas, White, Manson, et al., 2003; Mullington et al., 2009), diabetes (Ayas, White, Al-Delaimy, et al., 2003; Knutson et al., 2007; Reutrakul & Van Cauter, 2018; Spiegel et al., 2005), stroke (Foley et al., 2004; Qureshi et al., 1997), obesity (Cappuccio et al., 2008; Knutson et al., 2007; Reutrakul & Van Cauter, 2018), and mortality (Hublin et al., 2007).

Overall, cognitive control has been associated with both emotion regulation and sleep, and poor sleep quality has also been identified as a risk factor for developing depression (Baglioni et al., 2011). This suggests that together, poor sleep quality and working memory deficits disproportionately influence the development of depressive symptoms.

Poor sleep quality has been shown to increase the likelihood of developing depression and affect physiological and cognitive performance, with important downstream impairment to completion of daily tasks (Dzierzewski et al., 2018; Naismith et al., 2009; Robert D Nebes et al.,
Due to the way in which sleep functions as a regulatory resource, it follows that sleep should be examined within this context. Poor sleep can lead to a multitude of risk factors and is associated with an increased likelihood of developing depression, and it is therefore necessary to include as part of the framework for understanding the mechanisms underlying these relationships.

**Primary Goals and Hypothesis**

Together, the extent literature discussed in this paper provide initial support for the role of sleep quality, as well as working memory, as crucial emotion regulation resources. When considering this from the SOC-ER framework, it is necessary to understand how well older adults select and optimize emotion regulation given their available resources. It is also important to understand how this process occurs when emotion regulation resources become less available, such as with age-related changes in sleep quality and cognitive decline. Given that a significant amount of extant literature has examined these relationships cross-sectionally (de Almondes et al., 2016; Robert D. Nebes et al., 2009; Yu et al., 2016), the current study aimed to extend previous findings by elucidating how these variables function longitudinally through an examination of intra and interindividual effects. To represent these goals, the conceptual model represented by Figure 6 was proposed.

The primary goal of this study was to demonstrate the longitudinal relationships between sleep quality and depressive symptoms as well as between working memory and depressive symptoms. Specifically, it is hypothesized that subjective sleep quality and working memory will both negatively predict depressive symptom expression over time.
CHAPTER TEN: STUDY 3 METHOD

Participants

Data from the Health and Retirement Study (HRS) was utilized. This longitudinal dataset is sponsored by the National Institute on Aging and collected through the University of Michigan. Participants provided informed consent in accordance with the procedures of the University of Michigan Institutional Review Board, and the present study was approved by the University of Central Florida Institutional Review Board. Data have been collected every two years since 1992 and consists of randomly selected participants, with additional information on HRS design and collection methods found in published reports (Hauser & Willis, 2004; Weir et al., 2016). This study utilized waves 6 (2002) through 12 (2014), including 9,935 participants of the total HRS database’s 42,053 participants who were age 65 and older and included the necessary sleep data (see Figure 7).

Measures

Demographic variables

Age, biological sex, and race were self-reported by the participant. Race was recoded to White and non-White to protect the identity of participants, as specifying race (i.e., Native American and Pacific Islander) and age of some older adult participants would pose greater than necessary risk of identification. Education was assessed as self-reported years of formal schooling completed. All variables that were included in analyses were mean centered with the exception of CES-D.

Working Memory
Working memory was represented using the Serial 7’s test, which requires participants to subtract seven from 100 and each subsequent sum (i.e., 100-7, 93-7, etc.) for a possible score. References and measure descriptions for this measure can be accessed online (Hauser & Willis, 2004; Weir et al., 2016).

**Depression**

Depression was measured using a shortened version of the Center for Epidemiological Studies Depression (CES-D) measure (Radloff, 1977). The shortened CES-D is a dichotomized (yes/no) eight question measure with a possible score range from zero to eight, though due to reduce covariance, the question about sleep was removed from the measure, leaving a possible score range from zero to seven. All positive items were reverse scored. The original measure has demonstrated both high internal consistency (Cronbach’s alpha .85 to .90), and validity (Radloff & Teri, 1986) among older adults. The shortened CES-D’s internal consistency was slightly lower (Cronbach’s alpha .81) For the purposes of this study, CES-D was treated as continuous despite having a cutoff score that indicates probable depression (Koenig & Blazer, 1992).

**Sleep**

Based on the approach used in a study by Min and colleagues (2016), a sleep quality composite score was calculated using the following questions from the HRS: (1) “How often do you have trouble falling asleep?” (2) “How often do you have trouble with waking up during the night?” (3) “How often do you have trouble with waking up too early and not being able to fall asleep again?” (4) “How often do you feel really rested when you wake up in the morning?” The responses were categorized as “most of the time = 1,” “sometimes = 2,” and “rarely or never = 3”. The fourth question will be reverse-coded before adding the values together so that lower scores indicate worse sleep quality. Overall, higher scores indicate better sleep quality.
**Statistical Methods**

Because missing data in longitudinal modeling is problematic and there was mortality-based attrition within the study population, full information maximum likelihood estimation (FIML) was utilized. This approach allowed for the estimation of model parameters despite missing data (McArdle & Hamagami, 1992), which reduced the underrepresentation of such individuals. The Robust Maximum Likelihood (MLR) estimator was used to improve parameter estimates. The *Mplus* software program (Muthén & Muthén, 2019) was employed for all analyses. The hypothesis was examined using hierarchical linear modeling as displayed in Figure 6. The proposed analyses controlled for biological sex, education, race (White versus non-White; Hispanic versus non-Hispanic).

This study utilized multilevel modeling (e.g., hierarchical linear modeling) to analyze the relationship between depressive symptom endorsement and both sleep quality and working memory over time (see Figure 6). There were two approaches to this multilevel analysis: the first examined the influence of within-person variations of variables including within subjects sleep quality, within subjects working memory, age, and wave on depression, and the second, which tested the effects of between-person variations on grand mean centered sleep quality, working memory, and the aforementioned demographic variables as covariates. All coefficients are unstandardized.
CHAPTER ELEVEN: STUDY 3 RESULTS

Demographics and Cognitive Performance

This study included 9,935 participants of the original 42,053 participants (see Figure 7). This sample was comprised of participants with an average age 75.42 (SD = 7.59) at the baseline wave (wave 6). The sample was predominantly female (57.57%), White/Caucasian (82.90%), non-Hispanic (92.92%), and completed an average of 11.74 (SD = 3.49) years of education (see Table 4).

Depressive Symptoms, Sleep Quality, and Working Memory

Results of the multilevel model indicated that at the within subjects level, depressive symptom endorsement increases over time ($b = 0.018, SE = 0.004, p < .001$) and with age ($b = 0.020, SE = 0.002, p < .001$). Further, at any given point in time, better sleep quality predicts lower depressive symptom endorsement ($b = -0.031, SE = 0.008, p < .001$). Similarly, regardless of time, better working memory ability predicts lower depressive symptom endorsement ($b = -0.036, SE = 0.006, p < .001$).

Results also indicated that at the between subjects level, better sleep quality is associated with lower depressive symptom endorsement ($b = -0.149, SE = 0.011, p < .001$), and better working memory is also associated with lower depressive symptom endorsement ($b = -0.165, SE = 0.011, p < .001$). In regard to covariates, there were significant associations between depressive symptom endorsement and education level ($b = -0.061, SE = 0.005, p < .001$), identifying as Hispanic ($b = 0.146, SE = 0.067, p = .029$), and biological sex ($b = 0.231, SE = 0.028, p < .001$), but not race ($b = -0.002, SE = 0.004, p = .951$).
CHAPTER TWELVE: STUDY 3 DISCUSSION

The primary findings of this study are that among older adults, depression increases over time and with age. Further, regardless of time, in relation to a person’s own average better sleep quality and better working memory both result in lower depressive symptom endorsement. A similar effect was demonstrated cross-sectionally, with associations between lower depressive symptom endorsement and both better sleep quality and better working memory. Results also indicated associations between lower depression and higher education, non-Hispanic nationality, being biologically male. These findings are consistent with past research. For instance, modest escalation in depression toward the end of life has been often reported (Roberts et al., 1997). It is also common for women to have a significantly greater likelihood of developing depression than men (Girgus et al., 2017), Hispanic individuals to report higher depression than non-Hispanic white individuals (Shetterly et al., 1996), and those with more education to report lower depression (Murphy & O'Leary, 2010). This research builds on past work by examining the combination of effects over 12 years in a large, demographically representative sample. However, what is particularly unique about the findings from the current study is demonstrating that changes or deviations from one’s own average of sleep quality and working memory are predictive of depressive symptom endorsement regardless of when the deviation occurs. These findings further support contextualizing later-life depression research within the SOC-ER model.

Though there are many possible resources that can be utilized for regulating depression, the current study demonstrated two important resources are conceptually interrelated to the selection, optimization, and compensation for emotion regulation framework that supports and expands past work (Opitz et al., 2012; Opitz et al., 2014). Specifically, this study demonstrates that when sleep quality and working memory are poor, it is more difficult to engage in the
process of selection, optimization, and compensation during the course of daily living, resulting in an inefficient approach to eliciting the desired emotion. Much like working memory, sleep quality serves as an internal emotion regulation resource, as it functionally aides in repairing adaptive processing, functional brain activity, and improves the integrity of the medial prefrontal cortex-amygdala connections (Vandekerckhove & Wang, 2017). In this way, better sleep facilitates and improves the capacity to regulate emotions that align with current goals. When these resources are functioning below what is optimal, this deterioration, in turn, results in experiencing increased undesired emotions.

As aging is accompanied by a reduction in the efficiency of cognitive functioning (Borella et al., 2008; Heinzel et al., 2017; Swanson, 2017) and overall quality of sleep (Ancoli-Israel, 2004), further research is needed to elucidate the effects of other variables contributing to their decline. Specifically, what is particularly concerning about these findings is that these resources do not exist in a vacuum. There are many other factors that can contribute to their decline with age and passage of time. One such contributing factor that could serve as a direction for future research is vascular burden. It is common for individuals to experience deficits in emotion regulation resources such as sleep quality (due to sleep apnea) and executive dysfunction related to vascular burden. In fact, recent findings have identified relationships between sleep disruption, inhibitory control (another aspect of executive function), rumination, vascular burden, and depressive symptom endorsement (Brush et al., 2020), which suggests there are likely additional factors to consider when conceptualizing mood disruption among older adults. By continuing to identify changes in emotion regulation resources, it will provide clinicians with a better framework for understanding the likely trajectory of their older adult patients, which is especially necessary given older adults are continuing to live longer.
Limitations

A potential limitation to the current study was the conceptualization of working memory. In the current study, working memory was represented by Serial 7’s total correct responses. Although this task has generally been described as a working memory task, it may not be as sensitive as other working memory tasks or a composite variable of multiple working memory tasks. Further, another potential limitation was the sleep quality assessment. While this sleep quality index includes items assessing domain-relevant, a longer, more widely-validated measure such as the Pittsburgh Sleep Quality Index may be preferable for future research.

In conclusion, these findings underscore the importance of both sleep quality and working memory as emotion regulation resources by identifying that as they deteriorate, individuals experience a greater propensity for developing depressive symptoms. The findings from this study elucidate specific and targetable emotion regulation resources to address during treatment, particularly among older adults who inevitably experience natural age-related declines in these resources with time. By continuing to identify changes and trajectories of over time, this will allow for treatments to identify and address specific emotion regulation resource deficiencies. As such, future research should consider examining other possible cognitive resources such as processing speed and inhibitory control. Future research should also consider comorbid medical conditions that are often associated with poor sleep and working memory, such as vascular burden and sleep apnea.
CHAPTER THIRTEEN: CONCLUSION

The primary goal of this series of studies was examine a representative population of older adults to elucidate the relationship between working memory and depressive symptoms, identify the degree to which working memory serves as a protective factor against depressive symptoms following the loss of a significant emotion regulation resource (i.e., spousal loss), and finally, test the inter- and intraindividual differences in depressive symptom endorsement relative to working memory ability and sleep quality. In doing so, the findings provided additional support for the SOC-ER model by identifying that working memory, spousal support, and sleep quality function as emotion regulation resources, and that changes in these resources can lead to inefficient emotion regulation over time. This is of particular concern given the natural tendency for age-related changes to result in the decline of each of these factors (Chui et al., 2015), and in turn identifies a diverse range of considerations that need to be accounted for in order to properly address the needs of older adults.

As has been discussed throughout this paper, aging is accompanied by a variety of adjustments due to naturally occurring decline. These changes lead to older adults experiencing a significant number of barriers to traditional care. Working memory is a cognitive skill often utilized in a variety of coping techniques that are taught as a part of psychotherapy for depression, specifically cognitive behavioral therapy (Opitz, 2013; Schmeichel & Tang, 2013; Schmeichel & Tang, 2015). Given that working memory decline is a barrier to such a commonly used depression treatment it is necessary for clinicians to assess their older adult patients’ neurocognitive functioning. Doing so will help tailor treatment to address patient needs more effectively. Also frequently overlooked is the quality of sleep that older adults experience. Treatment should focus on how to optimize sleep despite the age-related decline in quality, as it
can significantly affect mood as well as a myriad of other problems (Bruce & Aloia, 2006; Dzierzewski et al., 2018; Foley et al., 2004; Franzen & Buysse, 2008). Yet, sleep problems often go unreported and untreated among older adults (Miner & Kryger, 2017), which is particularly concerning due to variety of treatments available to improve sleep quality. Cognitive behavioral therapy for insomnia (CBT-I) is frequently used to address sleep problems; however, similar to psychotherapeutic intervention for depression, the underlying cognitive correlates may reduce the effectiveness of the treatment due to diminishing working memory ability among older adults. Despite that, CBT-I has been shown to be an effective treatment for older adults with MCI (Cassidy-Eagle et al., 2018) and provide similar short-term benefits as psychopharmacological interventions and even better long-term outcomes, especially when the protocol is modified based on individual needs, such as adjusting for cognitive deficits (Rybarczyk et al., 2013).

Another diverse aspect to consider is that of female biological sex. Older adult women tend to outlive their husbands, and approximately 40% of women over the age of 65 are widowed and experience emotional, physical, cognitive, and social decline as a result (Williams et al., 2007). Based on previous findings and the results of the present studies, women are at higher risk of developing depressive symptoms following spousal loss, which should be addressed by increasing the availability of care (Lundorff et al., 2017). While there are some available treatment options, these needs continue to be unmet. A meta-analysis examining interventions for spousal bereavement found that despite a variety of available treatments types such as emotional expression/psychosocial, psychoeducational, and mind-body focused, there were no advantages to these treatments compared to controls (Nseir & Larkey, 2013). Social support, however, has been identified as a resource that reduces depressive symptoms in those
experiencing bereavement and should therefore be made more readily available as a treatment option, such as in the form of widowhood support groups.

One final aspect of diversity that should be considered when approaching emotion regulation treatment among older adults is that the present study indicated that individuals who identify as Hispanic are at higher risk of developing depressive symptoms following the loss of a spouse. While the statistical significance of this small effect size may have been artificially inflated due to the large sample size, it is crucial to account for cultural differences in response to a loss. Studies have suggested that culturally based differences in the social support system structure may influence the degree to which an individual develops depressive symptoms following a loss (Choi, McDonough, et al., 2020; Choi, Shin, et al., 2020; Shin et al., 2018; Smith & Ehlers, 2020). Further research is needed, however, as identifying how the composition of an individual’s social structure may provide insight into the risk of depression development posed by the loss of a spouse. Although these considerations are informative for treatment, they require clinician understanding and integration into practice. Despite this, clinicians may not universally complete additional trainings about cultural factors that influence treatment outcomes (Hu et al., 2020). Nevertheless, these studies highlight the need for thoughtful consideration of a wide range of individual characteristics that healthcare providers must account for to provide effective treatment.
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† “Other” includes Pacific Islander and Native American
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Sex: 0 = Male, 1 = Female
Hispanic: 0 = non-Hispanic, 1 = Hispanic
Race: 0 = Caucasian, 1 = non-Caucasian
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† “Other” includes Pacific Islander and Native American
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† “Other” includes Pacific Islander and Native American
‡ ‡ CES-D score calculated without the sleep question
APPENDIX B: FIGURES
Figure 1: The longitudinal relationship between working memory and depressive symptoms.

The figure represents the conceptual dual change growth model for hypotheses 1-3.
Figure 2: Study 1 CONSORT diagram.
Figure 3: A slope intercept model of working memory’s effect on the trajectory of depressive symptoms following the loss of a spouse.

The figure represents the proposed conceptual model for hypothesis 4. Ragender = biological sex, rahispan = Hispanic/non-Hispanic, rarace = Race, raedyrs = education in years, lossage = age when the loss of spouse occurred, lw_m1_ser7 = serial 7’s score one wave prior to the loss of spouse, di = depression intercept, ds = depression slope, dq = depression quadratic, lw_cesd = CES-D score the wave the loss of spouse occurred, lw_p1-7 = plus 1-7 waves after the loss wave (i.e., one to seven waves after the loss).
Figure 4: Study 2 CONSORT diagram.
Figure 5: A slope intercept model of the results of working memory’s effect on the trajectory of depressive symptoms following the loss of a spouse.

*S7 = Serial 7’s Score. The duration between each wave is two years. Modeled at the mean, 1 standard deviation above, and 1 standard deviation below.*
Figure 6: A multilevel model demonstrating the longitudinal within-and-between-subjects effects of sleep quality and working memory on depressive symptom endorsement.

The figure presents the proposed hierarchical model used to examine study 3 hypotheses.
Figure 7: Study 3 CONSORT diagram.
August 18, 2020

Dear David Brush,

On 8/18/2020, the IRB reviewed the following protocol:

<table>
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<th>Type of Review:</th>
<th>Initial Study</th>
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<td>Title of Study:</td>
<td>A Longitudinal Examination of Working Memory, Sleep, and Depression Among Older Adults</td>
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<tr>
<td>Investigator:</td>
<td>David Brush</td>
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<tr>
<td>IRB ID:</td>
<td>STUDY00002139</td>
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<tr>
<td>Funding:</td>
<td>None</td>
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<td>Grant ID:</td>
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<td>• HRP-251-Form, Category: Faculty Research Approval;</td>
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The IRB determined that the proposed activity is not research involving human subjects as defined by DHHS and FDA regulations.

IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities are research involving human in which the organization is engaged, please submit a new request to the IRB for a determination. You can create a modification by clicking Create Modification / CR within the study.

Due to current COVID-19 restrictions, in-person research is not permitted to begin unless you are able to follow the COVID-19 Human Subject Research (HSR) Standard Safety Plan with permission from your Dean of Research or submitted your Study-Specific Safety Plan and received IRB and EH&S approval. Be sure to monitor correspondence from the Office of Research, as they will communicate when restrictions are lifted, and all in-person research can resume.
If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Kamille Birkbeck
Designated Reviewer
REFERENCES


https://doi.org/10.1097/01.mlr.0000156861.58905.96


https://doi.org/10.1037/dev0000727


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10.1037/pag0000227.supp (Supplemental)


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