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Everyday Memory: An Expanded View Of Autobiographical Memory Functions

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EVERYDAY MEMORY: AN EXPANDED VIEW OF AUTOBIOGRAPHICAL MEMORY FUNCTIONS

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CHAPTER 1 INTRODUCTION

Overview: Autobiographical Memory Functions

An autobiographical memory (AM) is a long-term, conscious remembrance of a personal experience within subjective space and time (Tulving, 1993, p. 67). It is about AMs that an individual *reminisces*—i.e., recollects and relays past experiences and events—either privately or with others (Baddeley, 1987; Bluck & Alea, 2002, 2011; Neisser, 1978). For much of its history, AM research followed one of two lines of inquiry. The first has largely addressed how accurately, efficiently, or veridically we remember our personal pasts; i.e., the *mechanics* of AM (Baddeley, 1987; Bluck, Alea, Habermas, & Rubin, 2005, p. 92; Bluck & Alea, 2011, p. 471). The second has been concerned with how AM processes begin and progress over the life span; i.e., the *development* of AM (Conway, Singer, & Tagini, 2004). However, when memory researcher and theorist Alan Baddeley argued in 1987 that too little AM research had posited, "What the hell is it for?," a new domain of memory research ensued. AM research began to investigate humans' application of AM and its purposes in everyday life; i.e., the *functions* of AM (Baddeley, 1987; Bluck & Alea, 2002, 2011; Neisser, 1978).

Early theorists of the functional approach posited two fundamental purposes of AM: evolutionary adaptability (Brown & Kulik, 1977), and "everyday," real-world utility (Baddeley, 1987; Neisser, 1978). However, as evolutionary research is intrinsically fraught with empirical impediments (Kihlstrom, 2009), the focus of AM research instead turned to identifying a set of theoretical purposes or function for which AM is used in "everyday" life (Bluck et al., 2005, p. 92). Early work in this area yielded three hypothetical functions: the Social function, the Directive function, and the Self function. The *Social* function addresses the use of AM to initiate social bonds, maintain relationships, and promote intimacy with another or others (Bluck &

Alea, 2002; Bluck et al, 2005). The *Directive* function concerns the use of AM to inform regulatory control, solve problems, develop and shape attitudes and opinions, and teach others lessons (Bluck & Alea, 2002; Bluck et al., 2005, pp. 93–94; Cohen, 1998; Kulkofsky & Koh, 2009, p. 459; Pillemer, 1998). The *Self* function reflects the use of AM to develop and maintain a culturally appropriate continuous sense of self over time (Bluck et al., 2005; Pillemer, 2009, p. 1198). Together, the three broad but comprehensive theoretical functions had vast explanatory appeal; so much so that the model went virtually unchallenged for nearly 40 years (Bluck et al., 2005). More recently, however, the model's lack of empirical validation fell subject to scrutiny; what little practical evidence did exist was insubstantial and often anecdotal (Bluck et al., 2005, p. 95). In response, researchers Susan Bluck and Nicole Alea (2011) developed a self-report scale for the express purpose of empirically validating the 3-function theoretical model. The Thinking About Life Experiences (TALE) scale was designed to quantitatively assess reminiscence behaviors underlain by the Social, Directive, and Self functions (Bluck et al., 2005, Bluck & Alea, 2011). Results of the TALE yielded compelling evidence for the existence of the 3-function model (Bluck et al., 2005; Bluck & Alea, 2011, p. 483). In both replication and subsequent scale validation studies, the TALE has consistently supported the 3-function model (Bluck et al., 2005; Bluck & Alea, 2011).

However, a common criticism of the TALE is that it is inherently self-referencing; it was developed to specifically validate the existence of the Social, Directive, and Self functions, thus its ability to detect and evaluate other potential functions is severely limited (Bluck et al., 2005; Bluck & Alea, 2011). Yet, this predicament was unavoidable; to validate a theoretical construct not yet empirically established necessitates that instrument development be driven exclusively by theory (Bluck & Alea, 2011). As such, other researchers (Kulkofsky & Koh, 2009; Robitaille, Cappeliez, Coulombe, & Webster, 2010; Webster, 1997) have developed scales informed, but not bound, by the 3-function model. Results of such studies suggest the existence of auxiliary AM functions in addition to or as constituents of the theoretical three (Hyman & Faries, 1992; Walker, Skowronski, Gibbons, Vogl, & Ritchie, 2009; Pasupathi, Lucas, and Coombs, 2002). Such findings emphasize both the need to expand existing views of current theory, and to improve methods of measurement. The alternative is to risk inadvertent ignorance of AM functions currently obscured by theory-centric techniques.

Thus recent research has taken an expanded approach by asking not only, “What the hell is it for?” (Baddeley, 1987), but “Where the hell does it come from?” (Kulkofsky & Koh, 2009, p. 459; Nelson, 1993). Well-established theory from the socio-developmental domain contends that AM functions “come from” person-environment interaction within and across time (Bluck, 2009, p. 1055; Kulkofsky & Koh, 2009, p. 459; Nelson, 1993). The argument that social and cultural contexts profoundly and unavoidably influence AM development and thus its use aligns well with widely accepted theories by Vygotsky (1978) and Bronfenbrenner (1979). However, to date, little empirical work on the influence of social and cultural contexts on AM development and use has been done. This is due in part to the nascency of empirical AM research; quantitative evaluations of AM functions have arguably just begun. But this is also due in part to the extreme empirical challenge of isolating real-time contextual factors that are by nature dynamic, ongoing, and interactive (Wapner, Demick, Yamamoto, & Minami, 2000, p. 2).

Recently, socio-cognitive developmental researchers Sarah Kulkofsky and Jessie Koh (2009) developed a scale designed to elicit a social context believed vital to the development of AM and its functions. Kulkofsky and Koh proposed that *joint reminiscence*—conversations with others about past remembrances—creates a social context within which AM socialization occurs

(Kulkofsky & Koh, 2009, p. 465). Kulkofsky and Koh's contention that AM develops early in childhood through joint reminiscing (Kulkofsky & Koh, 2009, p. 459; Fivush & Nelson, 2006; Fivush & Reese, 1992; Nelson, 1993) is well supported in the literature. Founded on the idea that development is embedded in the everyday social interactions between parent and child (Vygotsky, 1978), shared conversations of the past help children learn to evaluate and express past experiences and events (Wang, 2007). In this interactive context, children discover their place within social and cultural settings, which then influences the developing sense of self in relation to others (Wang, 2007). As the dynamic between emerging self, social context, and social cognitive capacities intensifies and matures, AM abilities arise (Doan, n. d.). Sociocultural influences then shape AM development in accordance with appropriate everyday use (Doan, n. d.; Wang, 2007).

To evaluate the AM functions reflected in everyday joint reminiscence, Kulkofsky and Koh developed the Caregiver-Child Reminiscence Scale (CRS) (2009). Administered to parents or other primary caregivers, the self-report CRS asks how often and for what reasons caregivers engage in "past talk" with their 3–4 year-old children (p. 462). In a validation study, the CRS partially mapped onto the 3-function theoretical model as measured with the TALE such that TALE Social function did not uniquely predict any CRS function, and no TALE function uniquely predicted the CRS Conversation or Peer Relationship functions (Kulkofsky & Koh, 2009, p. 465). Consistent with the theoretical CRS, the TALE Self function predicts the CRS Self function; the TALE Social function predicts the CRS Conversation and Relationship Maintenance functions; and the TALE Directive predicts the CRS Behavioral Control, Teaching/Problem-Solving, and Emotion Regulation functions. In addition, the CRS also yielded evidence for a fourth AM function, Cognitive Skills (skills necessary for the development of autobiographical remembering), which did not map onto any of the three theoretical functions as measured with the TALE (Kulkofsky & Koh, 2009, p. 460). This finding implied that, at least within joint-reminiscence contexts, the assumed theoretical model was in error. It also implied that the TALE had limited capacity to detect some functions not previously identified.

Results of the CRS validation study thus produced evidence that the joint reminiscence context elicits AM functions previously obscured by the theory-centric TALE. As such, CRS offers AM researches a springboard from which to generate novel hypotheses with greater specificity than permitted with the TALE. However, the CRS fails in two ways to have broad research appeal and utility. One, the CRS was designed for child-caregiver dyads to investigate developmentally relevant AM functions (Kulkofsky & Koh, 2009). It is therefore inappropriate for use with adult samples to garner frequencies and types of adult joint reminiscing. Two, a vital influence on joint reminiscing and thus AM socialization is the cultural context (Kulkofsky & Koh, 2009). Theory and evidence from multiple psychology and human ecology domains suggest the differential use of AM functions across ethnic, race, and culture groups (Doan, n. d.; Miller, Wiley, Fung, & Liang, 1997; Mullen & Yi, 1995; Wang, 2001; Wang, 2007; Wang & Fivush, 2005; Wang, Leichtman, & Davies, 2000). Examining cultural effects is empirically challenging, as ethnically diverse samples large enough for cross-cultural analyses are difficult to recruit (Bluck et al., 2005; Bluck & Alea, 2011; Kulkofsky & Koh, 2009). Such was the case for Kulkofsky and Koh, whose sample was culturally homogeneous (81.7% Caucasian; 10.4% Hispanic), precluding their testing for cultural effects (2009, p. 461). Thus, it is not known if the CRS instrument operates equivalently across ethnic groups let alone if ethnic groups show the similar levels of the different functions.

To overcome the limitations of the CRS, the current study adapted the CRS for use with adult samples and incorporated tests of cultural effects. The CRS measures the frequency with which caregivers engage in the past-talk behaviors with their young children within joint reminiscence contexts. The items of the adapted CRS (CRS-A) maintained the joint reminiscence context, but were rephrased for adult respondents who rate the frequency with which they engage in past-talk behaviors with nonspecific family and friends. Several analyses were conducted to establish the adapted scale and its psychometric properties. The CRS-A was also tested for construct (convergent and discriminant) validity with the TALE.

Background

The ecological tradition and everyday memory. The ecological perspective asserts that humans are situated within their environments, with which they are in perpetual interaction within and across time (Bluck, 2009, p. 1055). This is in contrast to the view that humans are strictly information processors, precisely recording the surrounding sensory information (Bluck, 2009, p. 1055). Therefore, remembering from an ecological approach is not about memory capacity, proficiency, or veridicality, but its utility in real-world contexts (Bluck et al., 2005, p. 92; Bluck & Alea, 2011, p. 471). Considering AM from an ecological perspective concerns why we remember the events of daily experience; i.e., what functions or purposes does AM serve in the carrying out of everyday life (Bluck, 2009, p. 1051; Bluck et al., 2005, p. 92). Essential to this idea is that contextual influences—e.g., personality, the social context, culture—are intrinsic elements of AM functions. AM function research that neglects to consider contextual elements is therefore manifestly incomplete.

The theoretical 3-function AM model. Since researchers first began formulating a theory of AM functions, the majority of hypothesized functions could be categorized into one of three broad functions: the Social function, the Directive function, or the Self function (Bluck, 2009, p. Bluck et al., 2005, pp. 93–94; Bluck & Alea, 2011, p. 471). The Social function concerns reminiscing to promote the initiation and maintenance of social bonds (Bluck et al., 2005, Bluck & Alea, 2011, p. 471; Kulkofsky & Koh, 2009, p. 459; Nelson, 1993). The content of Social function memories also provides substance for conversation (Bluck et al., 2005, p. 94; Bluck & Alea, 2011, p. 471). Conversation is a particularly important AM function, as it is a primary vehicle of socialization and joint reminiscing (Kulkofsky & Koh, 2009, p. 459). There is also evidence to suggest that the Social function is tied to empathy, such that sharing memories—e.g., commiserating with stories of similar experiences—facilitates the elicitation of empathic responses (Bluck et al., 2005, p. 94; Cohen, 1998). Contingently, recalling one's own autobiographical memories during social interactions in which the other's thoughts or feelings are ambiguous or unfamiliar facilitates perspective-taking (Alea & Bluck, 2003; Conway, 1996).

Given that the social nature of the joint reminiscence context induces some conceptual overlap with the other two theoretical functions, the *Directive* function concerns using the past to teach and inform, to guide future thoughts and behaviors, and to facilitate the inferring of thoughts and feelings of others (Bluck et al., 2005, p. 93). The Directive function is also vital to the formation of attitudes and beliefs (Bluck et al., 2005, p. 93). The ability to integrate knowledge of past experiences with new situations aids in problem solving, in updating perspectives, and in predicting future outcomes (Bluck et al., 2005, p. 93). Directive AM can inform what behavior or emotional response is socially and culturally appropriate (Bluck et al., 2005; Kulkofsky & Koh, 2009, p. 459; Webster, 1995).

Finally, the *Self* function concerns memories of self-knowledge and experiences that promote self-continuity and development (Bluck et al., 2005, p. 93). Reminiscences that serve the Self function are thought to be largely unconscious, such that they work automatically over time to update and maintain an ongoing sense of self (Bluck, 2009, 1054; Bluck & Alea, 2011, p. 471). This allows one to conceptualize a coherent past-to-present trajectory of one's self, which facilitates imagining and, ultimately making choices on behalf of, a future self (Bluck et al., 2005, pp. 93–94; Bluck & Alea, 2011, p. 471). This is in keeping with the assertion of Conway (Conway & Pleydell-Pearce, 2000; Conway et al., 2004) that although AM is constrained by past knowledge and immediate goals, it is nonetheless fluid across time and situation to ensure a stable sense self across multiple and invariant contexts. Thus, evidence suggests that normative uses of the Self function of AM include self-preservation (Bluck et al., 2005, p. 94), the promotion of positive self views (Bluck & Alea, 2011, p. 471), emotion regulation (Bluck et al., 2005, p. 94) and, a purpose particularly relevant to the ecological tradition, a culturally appropriate sense of self (Kulkofsky & Koh, 2009, p. 459).

Thinking About Life Experiences (TALE) scale. The 3-function AM model, although discussed at length in the theoretical literature and widely accepted, had until recently undergone little empirical scrutiny (Bluck et al., 2005, p. 94; Bluck & Alea, 2011, p. 472). To remedy, Bluck, Alea, Habermas, and Rubin (2005; and again by Bluck and Alea, 2011) developed the Thinking About Life Experiences (TALE) scale, originally a 28-item self-report instrument designed to investigate whether the theorized Social, Self, and Directive functions would hold empirically (Bluck et al., 2005, p. 91; Bluck & Alea, 2011, p. 472). Items were created based on the AM functions previously identified in the literature. The original 28-item TALE yielded four factors: Self-Continuity, Directive, Nurturing Relationships, and Developing Relationships; the latter two were characterized by the researchers as two subdimensions of the Social function. A later TALE replication study also conducted by Bluck & Alea (2011) resulted in a 15-item instrument that adhered to the theoretical Self-Social-Directive 3-function model (Bluck & Alea, 2011, p. 477). Initially, TALE construct validity was examined with respect to Big Five factors (John & Srivastava, 1999). As hypothesized, Extraversion converged with the Social function (Bluck & Alea, 2011, p. 480), but Extraversion was not strongly or significantly correlated with the Self or Directive functions to show discriminant validity (Bluck & Alea, 2011, p. 480). Also to show discriminant validity, the Big Five dimension of Neuroticism (emotional instability) was weakly and nonsignificantly correlated with the Self, Social, and Directive functions (Bluck & Alea, 2011, pp. 479–480). Although both the 28-item and the 15 items TALE scales were sufficiently validated, and the former replicated with the latter, the TALE is not without limitations (Bluck et al., 2005, p. 111–112; Bluck & Alea, 2011, p. 483; Pillemer, 2009, p. 1198). As previously discussed, the TALE was developed expressly to empirically validate the 3-function theoretical model, generating some controversy over its functional and conceptual utility (Kulkofsky & Koh, 2009; Pillemer, 2009, p. 1198). Likewise, the TALE items were not constructed to assess contextual effects (Pillemer, 2009, p. 1204), which would ground AM function research and theory in the ecological perspective.

Joint reminiscence. To empirically ground AM functions in the ecological perspective, and to investigate potential functions beyond the theorized Self, Social, and Directive (Pillemer, 2009, 1204), Kulkofsky & Koh (2009) examined AM functions through the framework of joint reminiscing. *Joint reminiscing* is the engaging in "past-talk," or talk with another about the past (Kulkofsky & Koh, 2009, 462). Joint reminiscing has been hypothesized as the context within which parent-child past-talk takes place (Kulkofsky & Koh, 2009, p. 459; Nelson, 1993).

Research suggests that joint reminiscence serve a predominantly Social function in early life, during which time joint reminiscing is a primary component of early memory socialization (Kulkofsky & Koh, 2009, p. 460; Neisser, 1978; Nelson, 1993). Joint reminiscing is also thought to become increasingly vital to the development of the Self and Directive functions as the individual matures (Kulkofsky & Koh, 2009). In fact, at least some AM researchers have posited that the self develops in narrative form, much like how autobiographical memories are verbalized for sharing with others (Fitzgerald, 1996; Friedman, Conway, et al., 2004; Neisser & Fivush, 1994). Findings from research in related domains that employ joint reminiscing paradigms imply differential use of AM functions. For example, if AM functions are elicited in joint reminiscing settings, then different styles of joint reminiscing known to exist between Chinese and European-American mother-child dyads should therefore differentially impact AM function frequency and type (Kulkofsky & Koh, 2009, p. 467; Kulkofsky, Wang, & Hou, 2008; Wang, 2004). For example, evidence of culturally differential joint reminiscence styles, European American mothers would be more likely use AM for a greater number of purposes, and employ the Social and Directive functions more frequently than would Chinese mothers (Kulkofsky et al., 2009; Kulkofsky & Koh, 2009, p. 467; Wang, 2004).

Four key capacities essential to AM development appear to be cultivated in the joint reminiscence context (Klein, German, Cosmides, & Gabriel, 2004, p. 465–466; Mullen & Yi, 1995, p. 408): *memorability* (identifying which types of events are or are not considered, at the family, societal, or cultural level, memorable); *temporality* (one's subjective place in time); *inferencing* (determining the causality of events or behaviors of self and others); and *articulating* (how to verbally relate experiences and memories). Because the objective of the TALE was to validate the broad theoretical model, it is plausible that past-talk behaviors specific to the needs of early AM development were inadvertently neglected.

Caregiver-Child Reminiscence Scale (CRS). To examine the possibility that the joint reminiscing context would elicit an expanded set of AM functions essential to AM development, Kulkofsky & Koh (2009) developed the Caregiver-Child Reminisce Scale (CRS). Given the capacities that children must acquire in order to successfully construct, store, retrieve, and relay autobiographical memories, an extensive set of potential CRS items were generated during a pilot study with 46 parents of 2- to 6-year-old children (Kulkofsky & Koh, 2009, p. 461). Principal axis factoring was used to select relevant items and determine their functions. Results showed evidence for not three, but seven functions, that only partially mapped onto the TALE (Bluck et al., 2005). Two versions of the CRS were presented. The first is the "validated" CRS, which was derived through factor analysis and shown in correlational and regression analysis with the TALE to have construct validity (2009, p. 465). The second is the "theoretical" CRS, which was not statistically validated by Kulkofsky and Koh, but which was promoted as reflecting "adult-like" AM functions (2009, p. 458). The theoretical CRS is presumed by Kulkofsky and Koh to have greater utility outside the developmental research domain than does the validated CRS. Kulkofsky and Koh also proposed that the theoretical CRS was better aligned with the TALE functions (2009, p. 467). Two CRS functions mapped onto the TALE Social function: Conversation (thinking and talking about the past to promote conversation) and Relationship Maintenance (thinking and talking about the past to develop and maintain social ties). Three CRS functions mapped onto the TALE Directive function: Behavioral Control (thinking and talking about the past to gain or maintain behavioral control); Teaching/Problem Solving (thinking and talking about the past to advise others or teach lessons); and Emotion

Regulation (thinking and talking about the past to gain or maintain positive emotionality). The seventh function to emerge was Cognitive Skills (thinking and talking about the past to develop AM memory skills). Cognitive Skills did not map onto any of the three TALE functions; instead, it was viewed as essential to the ability to joint reminisce (Kulkofsky & Koh, 2009, p. 461). Because validation of the CRS was conducted using a sample of predominantly Caucasian participants, tests for ethnicity/race invariance or investigations of cultural differences were precluded (Kulkofsky & Koh, 2009, p. 461).

Cultural self-identification. Research in AM and joint reminiscing has shown that, from a normative standpoint, children learn how to remember or reconstruct events in ways appropriate to and valued by the people in their sociocultural environment (Mullen & Yi, 1995). Thus, culture provides skill training and information about which AM functions are emphasized or valued (Mullen & Yi, 1995). Thus it is vital to thorough studies of joint reminiscing that information on individuals' ethnicity/race or cultural background be collected. However, although evaluating joint reminiscence and AM functions in terms of respondent ethnicity is vital, it is also important to understand the cultural context within which early AM capacities developed. Thus, parental ethnicity is of particular relevance when considering the effect of culture on joint reminiscing and AM development. The Revised Multigroup Ethnic Identity Measure (MEIM-R) (Phinney & Ong, 2007, p. 274) is an instrument designed to glean information on both individual ethnic identity formation, and such influencing factors as the ethnic affiliation of the respondent's mother and father.

Differential AM as a Function of Culture: Justification for Expanded Research

Fundamentally, the self in relation to others and across time is shaped within the context of culture (Vygotsky, 1978). Cultural norms, attitudes, beliefs, taboos, and practices inform appropriate behavior and thus social interactions (Fivush, 2011). The familial dynamic common to most cultures ensures that children learn the skills and develop the aptitude to be a functioning, productive member across the various levels of the social system of which the individual is a member (Bronfenbrenner, 1979; & Pleydell-Pearce, 2000; Fivush, 2011; Markus & Kitayama, 1991).

AM is a critical component of self in that it facilitates the development and sustaining of a cohesive self-concept (Conway & Pleydell-Pearce, 2000). However, cross-cultural research suggests that cultural influences on AM development foster socially appropriate behaviors (Fivush, 2011). For example, in individualistic Western cultures, where traits such as autonomy and self-mastery are valued, the "story of self" that emerges through AM reflects a life narrative consistent with such cultural assumptions (Fivush, 2011, p. 564). Contrarily, the life narratives of individuals from collectivist Eastern cultures would instead be founded on a concept of self as altruistic and selfless (Markus & Kitayama, 1991).

Evidence exists for broad cultural differences in self-conceptualization, especially with respect to the autobiographical narratives of adults from Eastern versus Western cultures (Fivush, 2011). In alignment with the differential cultural goals of AM, the autobiographical narratives of adults from Eastern cultures reflect collectivist values, such that more emphasis is placed on one's role within the sociocultural community (Fivush, 2011). Comparatively, the autobiographical narratives of adults from Western cultures tend to be more detailed, focused, and self-referential, in keeping with individualist ideals (Fivush, 2011). Research suggests that the construction of autobiographical narratives is facilitated during early development by caregiver reminiscing style (Fivush, 2011; Wang, Leichtman, & Davies, 2000). Joint reminiscences between caregiver and child therefore promote not only autobiographical narratives (Fivush, 2011), but also the AM content and skills that inform such narratives according to cultural expectations. For example, consider a caregiver whose joint reminiscence style is elaborative, detailed, and story-like. In this context, the child is encouraged to engage in and co-construct reminiscences; this situates the details of experience and events within the child's larger life narrative, which itself is situated within the caregiver and child's culture(s) (Doan, n. d.; Fivush, 2011). An elaborate reminiscence style fosters the child's AM and general memory skills (Doan, n. d.). Conversely, a caregiver whose reminiscence style is repetitive or low in *elaboration*—i.e., the caregiver engages the child in question-and-answer type dialogue about the past—results in AM skills that are comparatively deficient in terms of recall and narrative detail (Doan, n. d.).

Cultural differences in general memory are likewise relevant to the study of AM within the context of joint reminiscence. For example, the average age of first memories has been found to differ by as much as two years across cultures (Leichtman & Wang, 2005). This effect is hypothesized as being the result of caregiver conversation; i.e., the way that a caregiver jointly discusses life events with the child influences the way that the child remembers it (Leichtman & Wang, 2005). However, the degree to which a caregiver describes and details life events is considered to be a function of culture, such that the importance ascribed by a culture to the construction and retelling of memories influences caregiver conversational style to effect age of earliest memory (Leichtman & Wang, 2005).

Although cultural variations in AM functions have yet to be directly investigated, there is much evidence from related research to suggest that cultural factors differentially influence AM such that AM skills, content, and purposes vary across cultural groups. Additionally, that child-caregiver interactions have been shown to shape the capacity for and the way that we construct autobiographical narratives differentially across cultures, it is important that research examine cultural differences in AM functions.

Study Goals

The overarching goal of the current study was to ground AM functions in ecological theory by establishing joint reminiscing as an important socio-cultural context (Demick, Wapner, Yamamoto, & Minami, 2000, p. 213). Joint reminiscence is a common form of adult interaction and a highly appropriate context for the study of AM functions—a vehicle through which autobiographical memory develops within the sociocultural environment (Kulkofsky & Koh, 2009, p. 459; Nelson, 1993; Wang & Fivush, 2005). Therefore, both normative (how AM functions operate in everyday contexts) and causal (differences and similarities in AM function as a result of culture) perspectives were investigated (Demick et al., 2000, p. 213). Also tested were the utility and exhaustiveness of the underlying 3-function (Self, Social, Directive) theoretical model of AM functions long widely assumed, but for which empirical testing has been sparse (Bluck & Alea, 2011; Bluck et al., 2005; Kulkofsky & Koh, 2009).

The secondary goal of the proposed study was to validate an adapted version of the theoretical CRS for use with adult samples. The adapted scale, the CRS-A, underwent exploratory principal axis factor analysis followed by confirmatory factor analysis in order to specify the model and assess psychometric integrity. Additionally, gender and ethnic invariance tests (configural, metric/structural/factor loading, scalar/intercept, error variance, factor variance, factor covariance, and latent means) were conducted via the structural equation modeling approach proposed by Milfont & Fischer (2010). Multigroup CFAs were also run to evaluate the CRS-A's test-retest internal validity (Munro, 2005, p. 372). Finally, construct validity (convergent and discriminate) and method effects of the CRS-A were evaluated with multitrait-multimethod (MTMM) CFA analyses per the protocol proposed by Byrne (2013).

Hypotheses

In support of the goals specified above, four hypotheses were tested.

Hypothesis 1. It was hypothesized that the CRS-A, when administered to a diverse, college sample, would replicate the 7-function structure found in the original CRS sample. It was expected that factor analyses and psychometric tests on the CRS-A would yield results consistent with results of the original CRS.

Of particular interest to the current study was the emergence in the Kulkofsky and Koh (2009) validation of the Cognitive Skills function. The Cognitive Skills function (using past-talk to foster and cultivate the memory skills necessary to autobiographical remembering) was statistically supported by CRS data (Kulkofsky and Koh, 2009, p. 460, 466). However, Cognitive Skills did not map onto any of the TALE's three theoretical functions (Social, Directive, Self). As such, Kulkofsky and Koh characterized the Cognitive Skills function as one that was previously obscured, largely because the TALE, designed to empirically validate only the theoretical 3-function model, is unable to detect other functions (Kulkofsky & Koh, 2009, p. 465). Kulkofksy and Koh's discovery of auxiliary functions as elicited through joint reminiscing appears to support an expanded view of everyday autobiographical memory (2009, p. 465). However, because Kulkofsky and Koh also found evidence that Cognitive Skills past-talk diminishes as the child ages (Kulkofsky & Koh, 2009, p. 465), the current study was less certain that the Cognitive Skills function was as essential to adults as it was to young children.

Hypothesis 2. It was hypothesized that the CRS-A would perform equivalently across time, gender, and ethnic groups. Multigroup confirmatory factor analysis (MGCFA) was used to test configural, metric (structural/factor loading), scalar (intercept), error variance, factor variance, factor covariance, and factor means invariance (Milfont & Fischer, 2011). The following summarizes each specific multigroup hypothesis.

Hypothesis 2a, test-retest: It was hypothesized that the CRS-A would demonstrate invariance across time. No previous validation study for an AM-functions scale evaluated test-retest using CFA procedures. However, results of reliability-based tests of internal validity that were conducted on previous AM-functions scales suggested that the CRS-A would perform similarly across two consecutive academic semesters.

Hypothesis 2b, gender invariance: Although the original CRS (Kulkofsky & Koh, 2009) was not tested for gender invariance, gender invariance was found for a similar AM functions scale, the Reminiscence Functions Scale (RFS) (Robitaille et al., 2010; Webster, 1997). The RFS is a self-report scale that measures reminiscence frequency on eight AM-function dimensions, all of which have been validated for use with seniors, and some of which have been validated for use with adults in general. For those functions validated for all adults, the RFS was found to operate equivalently across gender groups.

Hypothesis 2c, ethnic/race/cultural invariance: Although no existing AM functions scale has been validated for cross-cultural invariance, related theory and empirical research from the socio-developmental domain suggest cultural differences in the use and application of AM functions (Bronfenbrenner, 1979; Conway et al., 2004; Conway & Pleydell-Pearce, 2000; Fivush, 2011; Leichtman & Wang, 2005; Markus & Kitayama, 1991; Mullen & Yi; Nelson, 1993; Vygotsky, 1978; Wang, 2004; Wang, Leichtman, & Davies, 2000). However, no evidence to date suggests that the functions themselves differ cross-culturally. It was therefore hypothesized that the CRS-A would demonstrate configural equivalency across ethnic/race/cultural groups, but no hypothesis was extended for metric equivalence or beyond. As such, results yielded from the testing of Hypothesis 2c were considered strictly exploratory.

Hypothesis 3. It was hypothesized that the CRS-A would map onto the three theoretical dimensions (Self, Social, Directive) of the TALE (Bluck et al., 2005; Bluck & Alea, 2011) when tested for construct validity using multitrait-multimethod (MTMM) CFA analyses. Although Kulkofsky and Koh (2009) did not examine the construct validity of the theoretical (adult-like) version of the CRS (which is the scale from which the CRS-A was adapted), correlation and regression analyses performed on the validated CRS demonstrated construct validity (convergent and discriminant) with the TALE. It was therefore predicted that the CRS-A would show convergent and discriminant validity with the TALE via a series of MTMM analyses as outlined by Byrne (2013): Correlated Traits/Correlated Methods (CTCM); NTCM (No Traits/Correlated Methods); Perfectly Correlated Traits/Correlated Methods (PCTCM); and Correlated Traits/Uncorrelated Methods (CTUM) (correlated traits, uncorrelated methods); and CTCM (correlated-traits, correlated-methods). Additionally, although MTMM analyses evaluate method bias, no AM functions scale to date has tested this psychometric property. The presence of method bias is indicated by large loadings on method factors, which MTMM analyses are designed to isolate (Marsh & Grayson, 1995, p. 181). However, because it is unknown if current AM functions scales demonstrate method effects, the test for method bias in the current study was considered exploratory, and no specific predictions regarding method factor loading values were made.

Hypothesis 4. Given the accumulation of evidence from related research domains that differences in AM function use are a function of ethnicity/race/culture (Doan, n. d.; Fivush, 2011; Kulkofsky & Koh, 2009; Nelson, 1993; Wang, 2004; Wang, Leichtman, & Davies, 2000), it was hypothesized that ethnic affiliation would predict differential effects in the frequency of AM function use. Also well documented in related literature is evidence that differences in caretaker reminiscence style are a function of culture (Leichtman & Wang, 2005). Thus, given the impact that early caregiver reminiscence style has on the socialization of AM, it was also hypothesized mother and father ethnicity would predict individual AM function frequency in alignment with patterns found at the group level. So although it was hypothesized (2c) that the CRS-A would demonstrate configural ethnic invariance, it is expected that functions are used with greater or less frequency depending on culture in general and parent ethnicity in particular.

It is important to note that all results yielded from the testing of Hypothesis 4 were considered both exploratory and provisional. First, results are necessarily *exploratory* because no direct evidence exists elsewhere, which precluded the current study from extending specific predictions. Secondly, results are necessarily *provisional* because, although not prohibited, the use of psychometric validation data for subsequent tests of psychological behavior is widely thought to contravene research best practices (Boslaugh, 2007). However, such findings are invaluable to the formulating of new hypotheses that can be tested with different samples and fresh data. As it is a hope of the current study that results prompt further research, as even provisional information is indispensible.

CHAPTER 2 METHOD

Participants

Participants were recruited for the current study exclusively through the electronic SONA research participation system at a large, urban Midwest research university. Response data for a total of 2238 participants were collected over the fall and winter semesters of the 2012–13 academic year. A total of 205 respondents replied “no” to the CRS-A question, “Do you engage in past-talk?" Per the protocol established for the original CRS (Kulkofsky & Koh, 2009), a response of "no" to this item disqualified that respondent's subsequent responses, necessitating removal of that case from the dataset. Of the 2033 cases that remained, 192 qualified as retest cases (collected winter 2013), and were pulled from the dataset for separate test-retest analysis. The final sample consisted of 1841 unique cases.

Detailed age information was unavailable at the time of data collection, but a total of 1811 (98.4%) of respondents selected "Yes" to the question, "Are you over 18 years of age?" Additionally, respondents were assumed to be largely of traditional college age, as SONA samples have been comprised historically of undergraduates enrolled in introduction to psychology courses that require student research participation and/or that offer research participation extra credit. In terms of gender, 70.9% percent of the sample was female (*n* = 1305), 28.7% was male (*n* = 529), and 0.4% declined to answer (*n* = 7). In terms of ethnicity/race, 41.9% were Caucasian (*n* = 771); 24.5% were African-American/Black (*n* = 451); 13.5% were Arab/Middle Eastern (*n* = 249); 9.3% were Asian (*n* = 171); 3.3% were Hispanic (*n* = 60); 3.4% were Multiracial (*n* = 63); 0.30% were Native American (*n* = 6); 0.20% were Hawaiian/Pacific Islander (*n* = 4); 2.1% were Other (*n* =39); and 1.5% declined to answer (*n* = 27). Table 1 summarizes the current study's demographic information.

All items for the current study were included on the SONA prescreen questionnaire, for which participants received 0.50 credit upon survey completion. No monetary compensation was offered in lieu of credit hours per conducting university guidelines. The prescreen questionnaire was available in English only.

Instruments

In addition to age, gender, and ethnicity demographic items, a total of 77 items from three behavioral scales were included as part of the SONA mass presecreen for a total of two consecutive semesters. All items featured either Likert-type frequency rating schemes, multiple choice, or fill in the blank response options. The prescreen questionnaire was accessible exclusively online and available to participants 24 hours per day, 7 days per week, and from any location with online access providing that a participant had an active student login with the conducting university's online system. A mobile version of the proposed questionnaire was not available. The entire prescreen questionnaire was estimated to take 15–30 minutes to complete on average (SONA Research Guide, 2012).

General demographic items. Demographic information collected for the current study included age (< 18, ≥ 18); gender (Male, Female, Decline to Answer); and ethnicity/race (Caucasian, Black/African-American, Arab, Asian, Multiracial, Hispanic, Native American, Native Hawaiian/Pacific Islander, Other; Decline to Answer). Detailed age information was unavailable for the two semesters over which current study was active. Demographic information is summarized in Table 1.

Scale 1: CRS-A: Adult-like autobiographical remembering functions in the joint-reminiscence context. The CRS-A is a 41-item scale (plus two qualifying questions) adapted for adult samples from the theoretical version of the 7-function Child-Caregiver Reminiscence Scale (CRS) developed by Kulkofsky and Koh (2009). Per the theoretical CRS, seven functions (Conversation, Relationship Maintenance, Behavioral Control, Teaching/Problem Solving, Emotion Control, Self, and Cognitive Skill) were found to underlie 38 past-talk behaviors. Additionally, six of the seven CRS functions mapped onto the Social, Directive, and Self functions of the TALE (Bluck et al., 2005). Figure 1 illustrates the conceptual CRS model and its relation to the TALE. Table 2 summarizes the items and functions of the theoretical CRS.

Of note: Although both the “validated” CRS and the “theoretical” CRS each feature and expanded set of seven AM functions, the two versions differ in other important ways. The “validated” version is the product of principal axis factoring and correlational analyses with the TALE. It is thus the version validated for use with child-caregiver samples for investigations of the AM functions relevant to early development (Kulkofsky & Koh, 2009). Its functions are Conversation, Peer Relationships, Directive, Emotion Regulation, Positive Emotionality, Individual Self in Relation to Others, and Cognitive Skills. No TALE function uniquely predicted the CRS Conversation, Emotion Regulation, or Cognitive Skills. The TALE Self function uniquely predicted the CRS Self, Peer Relationships, and Positive Emotionality functions. The TALE Directive function uniquely predicted the CRS Directive function. As such, the “validated” only partially mapped onto the TALE (2009, p. 465). Figure 2 depicts the conceptual CRS validated model.

Contrarily, the “theoretical” CRS was not validated by statistical analyses; instead, the theoretical CRS was presumed by Kulkofsky and Koh to reflect “adult-like” functions outlined in the theoretical literature (2009, p. 458). The theoretical CRS features the seven functions described previously. Most items from the validated CRS maintained their phrasing for the theoretical CRS, but there were minor differences. Table 3 summarizes the CRS items, their theoretical AM functions, their AM validated functions, and their validated factor loadings. Because the current study was interested in an expanded view of AM functions for *adults*, only items from the theoretical CRS were adapted. Table 4 lists the CRS-A as administered to participants in the current study.

To improve the chances of replicating the results of the CRS, the same Likert-type rating response scheme used by Kulkofsky and Koh (2009) was implemented for the CRS-A. Respondents were presented with the instruction, “We are interested in how and why people engage in *past-talk*. Past-talk is conversation about events that you have experienced with the person(s) you are speaking to or that you have experienced but your conversational partner(s) have not. Please keep past-talk conversations in mind when answering the following questions.” Two general questions were then asked: “Do you engage in past-talk?” (Yes/No), and “How often do you engage in past-talk?” Items are in response to the stem statement, I engage in past-talk with myself and/or others in order to…” Respondents then rate the frequency with which they engage in the past-talk behaviors on the following 7-point Likert-type scale (1 = almost never; 2 = rarely; 3 = seldom; 4 = occasionally; 5 = sometimes; 6 = often; 7 = very often) (Kulkofsky & Koh, 2009, p. 462). The validated CRS has an internal consistency ranging from .85 for the Conversation and Cognitive Skills subscales to .90 for the Emotion Regulation subscale (Kulkofsky & Koh, 2009, p. 464). Per the Kulkofsky and Koh paradigm, cases corresponding to respondents who answered “No” to the, “Do you engage in past-talk” question were removed from the dataset.

Scale 2: TALE: Autobiographical remembering functions in a generalized context. The convergent and discriminant validity of the CRS-A will be tested in association with the Thinking About Life Experiences (TALE) scale (Bluck et al., 2005; Bluck & Alea, 2011). There exists both a validated 28-item TALE (Bluck et al., 2005) and a validated 15-item TALE (Bluck & Alea, 2011). The 28-item TALE was used by Kulkofsky and Koh (2009) to test the construct validity of the CRS. However, so as not to overburden the SONA prescreen questionnaire, the 15-item TALE was used in the current study. Both scales have been validated for use with a young adult population (Bluck & Alea, 2011, p. 472). Respondents are presented with the instructions, “Sometimes people think back over their life or talk to other people about their life: It may be about things that happened quite a long time ago or more recently. We are not interested in your memory for a particular event, but more generally in how you bring together and connect the different events and periods of your life. Please select a response to answer these two questions: “In general, how often do you think back over your life?” and “In general, how often do you talk to others about what’s happened in your life?” Next we present a variety of situations. Please select one response on each scale to indicate how often, when you think back about or talk about your life, you do it for the reasons given. There are no right or wrong answers. Do not hesitate to use any of the points on the scale. If you never think back over your life for this reason, select, ‘Almost never.’ Please answer every question.” Items are in response to the stem statement, “I think back over or talk about my life or certain periods of my life…” Respondents rate the frequency with which they engage in the TALE reminiscence behaviors on the following 5-point Likert-type scale: (1 = almost never; 2 = rarely; 3 = occasionally; 4 = often; 5 = very frequently) (Bluck & Alea, 2011, p. 473). The TALE has an internal consistency ranging of .74 for the Social subscale; .78 for the Directive subscale; and .83 for the Self subscale (Bluck & Alea, 2011, pp. 477–478). The TALE has thus far been validated with largely Caucasian samples (Bluck & Alea, 2011, p. 472). The TALE items with their matching functions can be found in Table 5.

Scale 3: MEIM-R: Revised ethnic identity measure. The degree to which ethnic identity has been assimilated can be measured with the Multigroup Ethnic Identity Measure-Revised (MEIM-R) (Phinney, 1992; Phinney & Ong, 2007). The six-item MEIM-R has been validated for use with a diverse, adult population (Phinney, 1992; Phinney & Ong, 2007). The

MEIM-R's items correspond to two ethnic identity subscales: Commitment/Attachment—affection, a sense of belonging, and personal investment (Phinney & Ong, 2007, p. 272), and Exploration—seeking ethnicity-oriented or –influenced information or experiences. However, the two dimensions can be collapsed to compare MEIM-R scores across ethnic groups (Phinney & Ong, 2007, p. 272, p. 279). Respondents are presented with instructions, "In terms ethnic group, what is your father's identity," and "In terms of ethnic group, what is your mother's identity?" Respondents in the current study were asked to select one of the nine SONA ethnicity/race categories (1 = Caucasian; 2 = African-American/Black; 3 = Arab/Middle Eastern; 4 = Asian; 5 = Hispanic; 6 = Multiracial; 7 = Native American; 8 = Hawaiian/Pacific Islander; 9 = Other; 10 = Decline to Answer). Although not evaluated in the current study due to irrelevance to hypothesized effects, remaining MEIM-R questions were presented to respondents who rated the frequency with which they engaged in MEIM-R behaviors on the following 5-point Likert-type scale (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree) (Phinney & Ong, 2007, p. 276). Internal consistency of the MEIM-R is .76 for the Exploration subscale, .78 for the Commitment/Attachment subscale, and .81 for the combined scale (Phinney & Ong, 2007, p. 277). The revised MEIM's items per subscale can be found in Table 6.

Procedure

Participation in SONA online studies requires an active university student account with which access to the SONA system is granted. Once logged into SONA, participants enrolled in participating psychology courses are presented with a list of active studies. Students are instructed that to participate in a study, the SONA prescreen must be completed first. Upon clicking the link to access the prescreen questionnaire, informed consent (Appendix A) is displayed. Participants are informed that by completing the prescreen questionnaire he or she is agreeing to participate. If the participant chooses to continue, an introduction to prescreen and a set of general instructions (Appendix B) is displayed. Participants are prompted to click to access the questionnaire. The SONA prescreen features a standard set of demographic questions plus questions specific to active studies that have pre-approved by the conducting university's psychology department and IRB for inclusion on the prescreen. Upon prescreen completion, 0.5 credit hour is electronically allocated to the participant's SONA account for application toward research requirements and/or extra credit in participating undergraduate psychology courses.

Data Collection

The current study collected data from 77 scale items plus three demographic items (over/under 18, gender, and ethnicity), all of which were included on the SONA prescreen for two consecutive academic semesters. Throughout the semesters for which the current study was active, the study's principal investigator downloaded and checked response data for accuracy and potential technical issues. The purpose of collecting data over the second semester was for the purpose of retest (internal validity). During the second semester, a total of 192 qualifying retest cases were collected. Retest respondents who answered, "No" to the "Do you engage in past-talk" qualifying question were removed from the dataset per the protocol established by Kulkofksy and Koh (2009).

All data for the current study were downloaded by the principal investigator into Excel (version 14.3.9) for Mac 2011 (Microsoft, 2011). Data were then transferred to SPSS 21 (IBM Corp., 2012). SPSS data files were then imported into LISREL 9.1. (Scientific Software International, 2012) for the purpose of creating LISREL Data files. All data and analyses files were securely stored on the principal investigator's personal laptop.

Data Analyses

The following data analyses were conducted for the current study. Prospective power analysis using G*Power© (Buchner, Erdfelder, Faul, & Lang, 2009); datascreening and preliminary demographic analyses differences tests using SPSS 21 (IBM Corp., 2012) and LISREL 9.1 (Scientific Software International, 2012); exploratory factor analysis (EFA) as principal axis factoring (PAF) using R-Factor (Basto & Pereira, 2012); and confirmatory factor analysis (CFA) using LISREL 9.1 (Scientific Software International, 2012). Additional validation analyses run in LISREL 9.1 included multigroup CFA (MGCFA) invariance tests, and, using TALE (Bluck et al., 2005; Bluck & Alea, 2011) response data, multitrait-multimethod (MTMM) tests of construct validity and method effect. The alpha set for all significance tests was .05 unless otherwise stated. All analysis procedures and results are detailed in the Results section.

CHAPTER 3 RESULTS

The following details the results of the current study's analyses as outlined in the Data Analysis section.

Prospective Power Analysis

Figure 3 depicts the results of the prospective power analysis conducted for the EFA. The prospective power analysis was based on the following values: $\alpha = .05$, w = degrees of freedom, and effect size. Alpha (Type I error risk) was set at .05. Degrees of freedom were estimated using the formula p(p + 1)/2 (Raykov & Marcoulides, 2006, p. 36), where p = number of scale items. For the CRS-A, p = 41, therefore 41(41 + 1)/2 = 861. An estimated effect size of .90 was used per MacCallum Browne, & Sugawara, 1996 as the lowest acceptable estimates for the Comparative Fit Index (*CFI*) and Non-Normal Fit Index (*NNFI*). Results recommended a minimum $n_{\text{EFA-ESTIMATED}} = 182$. That the actual EFA sample ($n = 921$) was more than five times the recommended n cautions that EFA may be overpowered. This is of concern primarily in terms of the model chi-square, which is widely accepted as a fundamental test statistic for structural equation modeling despite its sensitivity to large sample sizes (Hooper, Coughlan, Mullen, 2008, p. 56). Thus multiple fit indices (e.g., ratio of chi-square to degrees of freedom, *CFI*, *NNFI*, *RMSEA*, and *SRMR*), as well as essential model features such as error plots and squared multiple correlations (Hooper et al, 2008, p. 56), were evaluated in combination to determine the fit of all current study models (see Appendix C for details regarding goodness-of-fit and subjective fit indices used in the current study). The power analysis was run using G*Power© (Buchner, Erdfelder, Faul, & Lang, 2009).

Because most classic psychometric tests are considered to have sufficient power if the datasets on which they are derived have shown sufficient power with CFA analyses (MacCallum et al., 1996), no further prospective power analyses were run for the remaining model tests.

Datascreening

Before running the EFA, CFA, MGCFA, and MTMM analyses detailed in the primary analyses subsections below, the entire dataset was screened for the following.

Qualification. Per the procedure established by Kulkofsky and Koh (2009), as a first step, 205 cases ($n_{F12} = 114$; $n_{W13} = 91$) out of a total of 2238 were removed due to participants answering “no” to the qualifying question, “Do you engage in past-talk?” Secondly, a total of 192 cases that qualified for retest were pulled from the main dataset, leaving a total of 1841 unique cases for all subsequent analyses.

Accuracy. The transfer of data from the SONA system to the statistical analysis program was verified as being complete. No data were out of range, and all means and standard deviations were plausible.

Missing data. All non-demographic prescreen items were forced choice; participants were required to respond to the current item in order to proceed to the next, resulting in no missing data. However, demographic items for age (< 18 or ≥ 18), ethnicity, whether or not the respondent has children, and whether or not the respondent is a trained childcare worker did allow the option, "prefer not to answer." Such cases were removed from MGCFA samples if applicable (e.g., gender invariance analyses).

Variance loss. An evaluation of coefficients of variation (standard deviations divided by mean) yielded no coefficients < .0001, indicating no undue variance was lost due to large mean values.

Univariate normality. All items were initially tested for univariate normality in LISREL 9.1 (Scientific Software International, 2012), then verified in SPSS 21 (IBM Corp., 2012). Table 7 summarizes the average *Z*-score skewness and kurtosis for all CRS-A items. *Z*-test skewness values > 1.96 are considered significant. Skewness is considered moderate when *Z*-values above 0 but below 1.5 (Forero, Maydeu-Olivares, & Gallardo-Pujol, 2009, p. 636). UV normality diagnostics also showed that the data were platykurtic—in some models, significantly so (see Table 7). Attempts to apply both square root and log nonlinear transformation techniques, which are recommended for negatively skewed and platykurtic data (Stevens, 1941), worsened nonnormality for all models, so analyses proceeded with untransformed data.

Multivariate normality. Multivariate (MV) nonnormality (skew and kurtosis) diagnostics were run also for each model using LISREL 9.1 (Scientific Software International, 2012). As summarized in Table 7, all models demonstrated moderate but nonsignificant MV kurtosis per Mardia's Relative Multivariate Kurtosis Index (Mardia, 1970, p. 528). Per Mardia's diagnostic, absolute index values > 1.96 indicate significant kurtosis different from 0. However, recent Monte Carlo studies have found Mardia's Index to underestimate MV kurtosis. Therefore, Mardia's Index should be considered in conjunction with results MV normality *Z*-test results (Gao, Mokhtarian, & Johnston, 2008; Jaccard & Wan, 1996, p. 74). As summarized in Table 7, results of the *Z*-tests of MV normality for all models indicate significant difference from 0 for skewness, kurtosis, and overall chi-square.

Outliers. Univariate (UV) and multivariate (MV) outlier diagnostics were run on the entire dataset (N = 1841) in SPSS 21 (IBM Corp., 2012). UV outliers occur when cases on a single variable are extreme. Scores for all cases were converted to *Z*-scores; by convention, *Z*-scores > ± 3.29 (α = .001) were flagged as potential outliers (Meriter & Vannatta, 2002, p. 28). Results indicated 11 cases (0.59% of the dataset), all on the CRS-A item 4, "I use past-talk to share my experiences with others," exceeded the recommended *Z*-score cutoff of ±3.29. However, because all scores on this variable were in range, the results of outlier diagnostics were strictly data driven. Given no other legitimate reason for dropping the flagged cases was evident, analyses proceeded with all cases in the dataset.

MV outliers occur when two or more variables include cases with extreme combinations of scores. Extremity is diagnosed using Mahalanobis Distance (MD), whereby MD values > ±3.29 (α = .001) constitute extremity (Meriter & Vannatta, 2002, p. 27). Results of the MD diagnostic revealed 1755 cases (95.32% of the dataset) to be MV outliers. Because removing such a large proportion of the dataset was unfeasible, it was decided that all cases would remain in the dataset.

Collinearity. Multicollinearity was evaluated for each CFA, MGCFA, and MTMM CFA model by comparing the condition number provided by LISREL 9.1 (Scientific Solutions International, 2012) against conventional cutoffs. The condition number reported by LISREL is analogous to the condition index provided for regression collinearity diagnostics in popular statistical programs such as SPSS (IBM Corp., 2012). Condition numbers of 1 indicate total orthogonality between indicators, condition numbers > 15 can indicate potential multicollinearity problems, and condition numbers over 30 can signify severe problems (Cohen, Cohen, West, & Aiken, 2004, p. 424). The majority of model condition numbers were within tolerable levels; however, the condition numbers for test-retest did approach the 30 cutoff. Likewise, squared multiple correlations > .95 can indicate multicollinearity (Grewal, Cote, & Baumgartner, 2004, p. 526). Although several models featured squared multiple correlations > .80, none were > .95. All multicollinearity results are detailed in each model's analysis subsection. Condition numbers are also included in the multigroup comparison summaries (Tables 14–16).

Exactly how multicollinearity impacts structural equation models is not well understood, especially within models featuring nonnormal distributions, multigroup comparisons, and/or correlated latent variables (Grewal et al., 2004, p. 528). Therefore, condition number values were recorded and taken into consideration when interpreting SEM results. Condition numbers for each model are reported in both the corresponding analysis subsection and multigroup change in chi-square comparison summaries (Tables 14–16).

Preliminary Analyses on General and Demographic Items

Before proceeding with item- and model-based analyses, the following tests were conducted to gauge the overall frequency of joint reminiscence behavior, both in general and from a demographic perspective, as well as to assess the reasonability of response data. Per the procedure established by Kulkofsky and Koh (2009), response frequencies to the item, “How often do you engage in past-talk?” (1 = Almost never; 2 = Rarely; 3 = Seldom; 4 = Occasionally; 5 = Sometimes; 6 = Often; 7 = Almost always), were tested for their ability to predict respondents’ ratings across on the 41 scale items. Results of linear regression analysis found that ratings in response to the general item, “How often do you engage in past-talk?”, significantly predicted respondent overall CRS-A scale scores for the 7-function model ($F(1, 1839) = 505.79$, $p < .001$, as well as the 6-function model ($F(1, 1839) = 532.99$, $p < .001$).

Respondents were asked to indicate their ethnicity/race in two slightly differently worded items: “What is your racial or ethnic background?,” which is the SONA default ethnicity/race item, and “Select my ethnicity,” which is from the MEIM-R (Phinney & Ong, 2007) for which respondents in the current study were asked to choose one of the nine SONA categories, which were identically labeled as in per the Demographics item. Results of bivariate correlations between demographic and MEIM-R response on each ethnic category showed that respondents were significantly consistent in identifying the same ethnic group across items: Caucasian, $r = .95$, $p < .001$; African-American/Black, $r = .98$, $p < .001$; Arab/Middle Eastern, $r = .89$, $p < .001$; Asian, $r = .96$, $p < .001$; Hispanic, $r = .98$, $p < .001$; Multiracial, $r = .88$, $p < .001$; Native American, $r = .72$, $p < .001$; Hawaiian/Pacific Islander, $r = .87$, $p < .001$; 9 = Other, $r = .47$, $p < .001$. Although significant, correlations were < .90 in five of nine categories. Because of this inconsistency, only the demographic item was used for all analyses necessitating ethnic identification information. The demographic item was chosen over the MEIM-R item because it preceded the MEIM-R item. It was therefore decided that respondents were likely more accurate when responding to the demographic item, whereas, MEIM-R survey items regarding personal ethnic commitment and exploration, as well as the ethnicity of the respondent's mother and father, may have inadvertently influenced differential response on the MEIM-R item.

Hypothesis 1 Analyses

Hypothesis 1 states that CRS-A will replicate the 7-function model of the CRS (Kulkofsky and Koh, 2009) when administered to an adult sample. The following sections address problems with initial replication attempts and the methods and analyses used to overcome them. Details regarding the definitions of and computations for fit indices used in the current study can be found in Appendix C.

Results of Initial Proposed EFA and CFA

Given that the CRS-A featured items from the theoretical CRS that had been reworded for administration to adult sample, to proceed to the confirmatory factor analysis (CFA) stage would have been premature. Although untested, there was indirect theoretical evidence in the literature to suggest that the seven functions and their items per the Kulkofsky and Koh (2009) theoretical model (see Table 2) would replicate with an adult sample (Kulkofsky and Koh, 2009, p. 458) given the appropriate instrument. The initial plan of the current study was to conduct an exploratory factor analysis (EFA) on one-half of the dataset (n = 921) using a structural equation modeling approach. That is, rather than evaluate the CRS-A data via factor analysis, Kulkofsky and Koh's 7-function theoretical CRS structure was assumed to be correct, and the data from the current study would be tested for goodness of fit within the assumed 7-function model. The results of the EFA would then be validated with a confirmatory factor analysis (CFA) using the remaining half of the dataset (n = 920). Successful solutions would justify further validation with multigroup CFAs (MGCFA) and multitrait-multimethod (MTMM) construct validity analyses. Table 2 reports the theoretical CRS items and their hypothesized functions. Items in Table 2 are organized according to their hypothesized CRS function, with each CRS function organized by its hypothesized TALE function. Table 4, which is organized in the same fashion as Table 2, lists the relation between the CRS-A items and their functions.

Attempts to replicate the 7-function model with the CRS-A by way of methods and procedures that aligned with those used by Kulkofksy and Koh failed to yield highly satisfactory solutions, so a different approach was taken. Results of the initial provisional EFA and follow-up CFA are detailed in Appendix D.

A Different Approach: Factor Analysis and CFA for Nonnormal Ordinal Data

There are two likely reasons why the CRS-A failed to replicate the theoretical 7-function CRS model (Kulkofsky & Koh, 2009). First, the objective of the CRS was to reveal those AM functions most relevant to the socialization of early AM development. The seven AM functions that Kulkofsky and Koh revealed did not, however, map onto "adult-like" functions predicted by theory (Kulkofsky & Koh, 2009, p. 458), so they proposed a theoretical, but unvalidated, 7-function model for adults. Because the current study was interested in exposing potentially obscured *adult* AM functions, the theoretical CRS seemed an excellent place to start. But because the theoretical CRS was not validated, it is not surprising that the current study was unable to replicate it, however theoretically germane.

Second, a desire to be consistent with Kulkofsky and Koh (2009) protocol overruled the current study's concern that methods and procedures used in the CRS validation study may not be entirely appropriate for the CRS-A validation study. For example, the Maximum Likelihood estimation conducted on Pearson's product-moment (PPM) matrices likely yielded misleading results; some possibly disadvantageous to the current study's objectives, but some possibly favorable (Basto & Pereira, 2012, p. 4; Bernstein & Teng, 1989; Gilley & Uhlig, 1993; Stevens, 1946).

To resolve, several changes at the measurement and estimation levels were adopted by the current study. Foremost, the data were subject to a new principal factor analysis (PAF) using R-Factor (Basto & Pereira, 2012). Unlike SPSS (IBM, Corp., 2012), which was used by Kulkofsky & Koh (2009), R-Factor allows for factor analysis based on polychoric (ordinal-to-ordinal) correlations, which produce more accurate results than PPM correlations with Likert-type data (Basto & Pereira, 2012). R-Factor also provides several factor extraction methods from which to determine the correct number of factors (Basto & Pereira, 2012). This is also an improvement over factor analysis in SPSS, which is limited to the Kaiser extraction method, known to overextract (Basto & Pereira, 2012). Details of R-Factor options and results used by the current study are found in Appendix E.

Results: EPAF. A series of EPAFs were conducted to determine optimal factor model for the CRS-A. To begin, a PAF forcing seven factors with all 41 items was conducted to test the replicability of the Kulkofsky and Koh (2009) PAF with adult sample data. Results of the multivariate normality tests verified the datascreening results. Data were both significantly MV skewed ($Z = 3785.46$, $p < .001$) and MV kurtotic ($Z = 18890.55$, $p < .001$). All EPAFs were run on a heterochoric correlation matrix. Based upon the Kulkofsky and Koh's use of an oblique rotation method, the forced 7-function solution was then run using Quartermax ($\delta = 0$; i.e., Quartermin). Items using the Quartermax rotation loaded on all seven factors. Per the Kulkofsky and Koh (2009) procedure, items with absolute factor loadings < .40 on any factor were dropped from the model.

All communalities were > .40. However, 70% of the communalities were > .60; with samples > 250, high communalities values provides some protection against overextraction. As expected, the oblique Quartermax rotation resulted in multiple cross-loadings; however, no item failed to have an absolute loading > .40. The Bartlett chi-square test of sample adequacy, for which a *n. s.* result is desired, was significant, $\chi^2(820) = 30577.42$, $p < .001$. However, with n = 921, significance is likely due to the sample being overpowered. Therefore, sample adequacy was verified with the *KMO* test, *KMO* = .96, where *KMO* > .60 indicates sample adequacy and values closer to 1.0 are best. The root mean square residual, at .024, fell well below the .05 cutoff, indicating good fit. Likewise, the ULS Goodness-of-Fit index also indicated good fit, *GFI* = .98, where > .95 is desired. However, the *GFI* is sensitive to sample size, so may be upwardly biased. The scree plot recommended somewhere between 4−10 factors. The extracted variance explained table showed that 70.22% of total model variance was being explained by seven factors—a 2.44% increases from variance accounted for by six factors, which was 67.78%.

Table 8 summarizes the loading patterns and values of the forced 7-function EPAF first using Varimax rotation, then verifying with Quartermax rotation. Results indicated that the loading pattern departed from the proposed Kulkofsky and Koh (2009) theoretical configuration.[1] What follows is an enumeration of those differences and possible explanations relevant to the adaption of the scale for adult samples.

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[1] As described elsewhere in this manuscript, Kulkofsky and Koh (2009) provided factor loadings and descriptives for the configuration that resulted from their PAF. However, the data-driven configuration does not align with their theoretical configuration, and some of the theoretical items were rewritten but not re-evaluated with a PAF. The CRS-A was adapted from the theoretical model. To attempt to obtain the true configuration of this scale, several PAFs with various rotation methods, both oblique (including Varimax) and orthogonal, were run. Because the use of Quartermax rotation was best supported in the literature as the rotation to use, its results were compared to the other PAFs only to get a sense of the true model from a PAF perspective. The model defined by the Quartermax rotation held, for the most part regardless of rotation method; in most cases, only the value of factor loadings changed. The most unstable items, in terms of factor affiliation, were those that belonged to the Cognitive Skills factor. At least two of these items, depending on rotation, switch signs and/or factor affiliation. Given that determining the best fit factor pattern of these items was unresolvable through PAF rotation, and

One, the items that in the Kulkofsky and Koh model loaded onto the functions of Behavioral Control and Teaching/Problem-Solving, respectively, loaded onto a single factor in the CRS-A PAF. There are several plausible reasons why this may have occurred, which are taken up in the Discussion section.

Two, also loading on the combined CRS-A factor of Behavioral Control and Teaching/Problem-Solving was the item, “I use past-talk to help lessen another’s negative emotions.” This item was part of Emotion Regulation in the Kulkofsky and Koh model. Per the CRS-A PAF, the item loaded on the combined factor strongly (.71) and positively (as did the other Behavioral Control/Teaching/Problem-Solving items). This is in contrast to the other Emotion Regulation items that all loaded negatively on the Emotion Control factor. As for what set this item apart from the others, it was the only Emotion Regulation item that specified “negative” emotions.

Three, two items that belonged to the Kulkofsky and Koh model function of Relationship Maintenance, “I use past-talk to help me understand others,” and “I use past-talk to understand how others feel about an event,” split off into their own factor. The nature of these two variables differs from the content of the other Relationship Maintenance items in that they are the only two Relationship Maintenance items that ask about the respondent in terms of “others,” versus “friends” or “family.”

Four, the item, “I use past-talk to bond with others,” which was a Relationship Maintenance item in the Kulkofsky and Koh model loaded on the CRS-A Conversation factor. The CRS-A PAF found that all Conversation items loaded positively on their factor, including

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that ultimately the CFA implied that Cognitive Skills was a superfluous factor that should be dropped from the model, the results of these additional EPAFs are not reported beyond the details found in the text.

this item from the otherwise negatively loaded Relationship Maintenance factor. In keeping with the interpretation of loading direction, people engage in joint reminiscence to bond with others when the opportunity to do so is already present. Also, like the two Perspective-Taking items, the "bonding" item refers only to "others"; thus it lacks the specificity of "friends" and "family" featured in the other Relationship Maintenance items.

Five, the item, "I use past-talk to remind myself of how far I've come and all the experiences I've had," which loaded in the Kulkofsky and Koh model as a Cognitive Skill, loaded on Emotion Control in the CRS-A model. This item was the most unstable in the model, switching factor affiliation with changes in rotation. That it loaded on Emotion Control in the Quartermax PAF is not readily explained. That it also loaded on Emotion Control in the Varimax rotation, albeit at a value below the acceptable absolute value cutoff of .40 (−.37) implies that it may not belong in the model.[2] Therefore, results of the CFA were examined for guidance on the fit of this item.

Six, although all loadings in the Kulkofsky and Koh model were reported to be positive, the current study found the items for CRS-A factors of Relationship Maintenance, Perspective-Taking, Emotion Regulation, Self, and Cognitive Skills were negative. Negative factor loadings imply that the item has an inverse relation with the factor (Bryant & Yarnold, 1995, p. 106).

Mean factor loadings were commensurate the Kulkofsky and Koh for those factors that appeared in both the theoretical and the statistically-derived models. The mean factor loadings using Quartermax rotation were as follows: Conversation = .54; Perspective-Taking = .75;

[2] Although .40 is fairly stringent, a loading of −.37 may suffice for some researchers because it reflects approximately 10% of shared variance between item and factor. When the loadings are for items rather than scales, this is especially true given that most items have lots of error relatively to true score variance. However, .40 was the cutoff used by Kulkofsky and Koh (2009) as well as Bluck and Alea (2011), so was used in the current study to maintain consistency.

Relationship Maintenance = .60; Behavior Control/Teaching/Problem-Solving = .58; Emotion Regulation = .65; Self = .59; and Cognitive Skills = .68.

Ordinal-reliability α for all factors was > .80, indicating high internal validity. Results were as follows: Conversation, α = .89, Perspective-Taking, α = .88, Relationship Maintenance, α = .93; Behavior Control/Teaching/Problem-Solving, α = .93; Emotion Regulation, α = .94; Self, α = .89; and Cognitive Skills, α = .91.

CFA of the 7-function solution. To test the feasibility of the forced 7-function EPAF configuration, a CFA using structural equation modeling was run in LISREL 9.1. As described in Appendix E, robust estimated least squares (RULS) was used instead of maximum likelihood (ML). In keeping with the oblique rotation used in the EPAF (Quartermax, δ = 0), CFA factors were allowed to correlate. Scale was set at 1.0 in the psi matrix per convention (Raykov & Marcoulides, 2006). Data were treated as ordinal. The *C3* (Satorra-Bentler) model chi-square used to calculate *RMSEA*, *NNFI*, and *CFI*, as it corrects for nonnormality.

Although there were some improvements in fit to suggest that the EPAF configuration was tapping into the true adult AM functions better than the Kulkofsky and Koh theoretical model. However, the overall model still demonstrated many of the same deficiencies found in the CFA that followed-up the provisional EFA.[3] This CFA was run using the same second half of the full data (*n* = 920) set as the CFA that followed up the provisional EFA, so there were no changes to the distributional properties previously reported. The condition number increased from 11.97 to 16.40, which was above the 15 cutoff. This could be an indication of increased

[3] Although only for the purpose of identifying problems in the model, MGCGAs (test-retest, gender, ethnicity) were also run on the forced 7-function model. Although the MGCFAs all held configurally, fit was consistently poor. Further constraints resulted in models failing to converge. As such, results of the 7-function analyses are only discussed to the extent that their failure justified and supported the establishment of the 6-function solution.

multicollinearity. However, the model is based on a PAF using Quartermin rotation, which purposefully strongly intercorrelates factors. All factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. Regression coefficients did stabilize somewhat: low $R^2 = .41$; high $R^2 = .87$).

Fit indices for the CFA further confirmed that the EPAF yielded a much better fitting model. Per the *C3* (Satorra-Bentler) test statistic, $\chi^2(758) = 3598.30$, $p < .001$. As before, it is likely that the significant chi-square is due to the sample being overpowered, rather than an indication of poor fit. The *RMSEA*, at .067 is much improved, and indicates adequate model fit. The χ^2/df ratio was 4.75 is also improved, as it is now below the "adequate to poor" cutoff of 5.0 (Byrnes, 1989, p. 55). Both the *NNFI* (.982) and the *CFI* (.983) indicated excellent fit. The Standardized Root Mean Residual (SRMR) dropped considerably, from .082 to .051, which was below the optimal < .08 (Hu & Bentler, 1999, p. 24). The normal probability (Q) plot showed that the residuals were substantially closer to the diagonal line; however, there remained sharp breaks on the ends that indicate either violations of normality, excess error, and/or the inclusion of unnecessary parameters (Raykov & Marcoulides, 2006, p. 33). The median standardized residual moved closer to the optimal of 0, from .280 to .103, with slightly less positive skew than in the previous CFA (range from −6.51 to +10.98). The number of standardized residuals < −2.00 dropped from 82 (10%) to 22 (3%); likewise for residuals > +2.00, down from 180 (21%) to 55 (7%). Although a huge improvement, the residual information and less-than-good fit still suggests that too many variables were included in the model (Raykov & Marcoulides, 2006, p. 49).

SEM reliability calculations indicated that all seven factors all exceeded the .70 cutoff to demonstrate high internal validity (Memon, 2012, p. 11): Conversation = .900; Perspective-

Taking = .834; Relationship Maintenance = .938; Behavioral Control, Teaching, and Problem Solving = .937; Emotion Regulation = .935; Self = .892; and Cognitive Skills = .900. As mentioned, SEM reliability calculation can lead to biased results when data are nonnormal (Basto & Pereira, 2012, p. 8). However, although the calculated values are somewhat higher for each factor than the EPAF's ordinal reliability α values, the pattern across factors is the same.

Per the average variance extraction calculations, the amount of variance accounted for by each function also exceeded the minimum recommended value of 50%: Conversation = 60.02%; Perspective-Taking = 71.50%; Relationship Maintenance = 65.29%; Behavioral Control, Teaching, Problem Solving = 62.28%; Emotion Regulation = 81.86%; Self = 78.87%; and Cognitive Skills = 83.01%. Again, the high values could reflect the additional variance accounted for by superfluous variables and/or factors (Cohen et al., 2004; Tabachnick & Fidell, 2007).

Addressing the "overexplaining" model. Although it is generally considered better to overfactor than underfactor (Fabrigar & Wegener, 2011, p. 60), overfactoring should also be avoided for its tendency to suggest constructs are statistically and theoretically spurious (Fabrigar & Wegener, 2011). The current study found evidence supporting a re-examination of the Kulkofsky and Koh (2009) 7-function theoretical CRS model. A number of changes were tested with the CFA in attempts to find the best item-factor affiliations to yield a suitable model; specifically, the multigroup models failed to converge. Modification indices, which are provided by LISREL (Scientific Software International, 2012) to facilitate model configuration, recommended only theta-delta correlations and other changes not supported by theory. Because subsequent hypotheses could not be tested unless multigroup models converged, a reconfiguration of the model was required to proceed.

The current study therefore sought to improve model fitness and suitability for multigroup by adjusting the number of factors, specifically, what impact the removal of the Cognitive Skills factor and related items would have on model fit. Cognitive Skills was chosen for the following reasons. Cognitive Skills was the only function in the CRS model that failed to map onto the TALE and its three theoretical functions of Social, Directive, and Self (Kulkofsky & Koh, 2009, p. 464). All other functions in the CRS expanded model, save for the CRS Self function, emerged as a subdimension of either the Social or Directive functions. As such, Cognitive Skills stood out as a potential artifact of Kaiser overextraction (Basto & Pereira, 2012, p. 5), thereby explaining indications of an "overexplaining" model. There was also evidence from the Kulkofsky and Koh study that the Cognitive Skills function loses relevance in adulthood. Although only marginally significant, Cognitive Skills was negatively correlated with child age, $r = -.12$, $p < .10$ (2009, p. 465). It was the only function in the CRS validated model that suggested a decrease in frequency of use as child age increased (Kulkofsky & Koh, 2009, p. 465). Finally, another autobiographical memory scale for older adults, the Reminiscence Functions Scale (Webster, 1995), which featured eight comprehensive functions, featured no Cognitive Skills-like function, nor any items that were got at Cognitive Skills AM behaviors. Therefore, the five adapted Cognitive Skills items ("I use past-talk to see how far back I can remember"; "I use past-talk to test my memory"; "I use past-talk to keep my memory and recall sharp"; "I use past-talk to remind myself of how far I've come and all the experiences I've had"; and "I use past-talk to improve my ability to convey my past experiences and memories to others") were removed from the model. Analyses were then rerun and the results examined for improvements.

Results: EPAF: 6-function model. An EPAF with the five Cognitive Skills items removed (item total = 36) was conducted on the EFA sample (n = 921). Table 9 summarizes the remaining 36 items and their AM functions. As with the forced 7-function EPAF, the correlation matrix was heterochoric and rotation was Quartermax ($\delta = 0$; i.e., Quartermin). Items using the Quartermax rotation loaded on six factors. As expected, the oblique Quartermax rotation resulted in multiple cross-loadings; however, no item failed to have an absolute loading > .40. Likewise, communalities were all > .40, with most (72%) > .60. This was a slight improvement increase from the 7-function EPAF, for which 70% of the communalities were > .60, indicating better protection against overextraction. Results of the multivariate normality tests verified the datascreening results. Also as expected, data without the Cognitive Skills items remained significantly MV skewed (Z = 3080.12.46, p < .001) and MV kurtotic (Z = 17621.75, p < .001). Chi-square tests of sample adequacy were all significant, Bartlett $\chi^2(820)$ = 26589.60, p < .00; Jennrich $\chi^2(820)$ = 123886.00, p < .001; Steiger $\chi^2(820)$ =5733.29, p < .001. However, with n = 921, significance is likely due to the sample being overpowered rather than any true difference in models. Therefore, sample adequacy was verified with the *KMO* test, which held at *KMO* = .96 (*KMO* > .60 indicates sample adequacy and values closer to 1.0 are best). The root mean square residual increased slightly, from .024 to .026, but remained well below the .05 cutoff. The ULS Goodness-of-Fit index also held at *GFI* = .98, above the > .95 to indicate excellent fit (however, the *GFI* is sensitive to sample size, so may be upwardly biased). The scree plot was more definitive than with the 7-function EPAF, indicating that the ideal number of factors is 6–8 (as mentioned before, the scree often overextracts). The amount of variance explained with six factors was 69.66%.[4] Additionally, only five of the eigenvalues surpassed 1.0 (accounting for 67.09% of the variance in the model). However, the eigenvalue for factor 6, at .93, was closest to

[4] For comparison, the variance explained in the 7-function model, which featured 41 items rather than 36, was 70.22%.

1.0, suggesting that the 6-function model was a better fit for the CRS-A data than eigenvalue for factor 5, which was 1.3. Table 10 summarizes the loading patterns and values of the 6-function EPAF. Results indicated that the item-factor affiliation patterns that emerged from the 7-function EPAF held despite the removal of the Cognitive Factor items.

The mean factor loadings reported in the 7-function EPAF held in the 6-function model with the exception of Emotion Regulation, which increased from .65 to .72, likely due to the removal of the Cognitive Skills item, "I use past-talk to remind myself how far I've come and all the experiences I've had." This was the most erratic of the Cognitive Skills item; it changed factor affiliation with every rotation method. The mean factor loadings were as follows: Conversation = .54; Perspective-Taking = .75; Relationship Maintenance = .60; Behavior Control/Teaching/Problem-Solving = .58; Emotion Regulation = .72; and Self = .59.

Ordinal-reliability α remained > .80 for all factors in the 6-function model, indicating high internal validity. Results were as follows: Conversation, α = .89, Perspective-Taking, α = .88, Relationship Maintenance, α = .93; Behavior Control/Teaching/Problem-Solving, α = .93; Emotion Regulation, α = .95; and Self, α = .89.

CFA of 6-function solution: Model 1. To validate the EPAF 6-function configuration, an SEM CFA using RULS estimation was run in LISREL 9.1 (Scientific Software International, 2012). CFA factors were allowed to correlate in keeping with the oblique rotation used in the EPAF (Quartermax, δ = 0). Scale was set at 1.0 in the psi matrix per convention (Raykov & Marcoulides, 2006). Data were treated as ordinal. To correct for nonnormality still present in the 6-function model, the *C3* (Satorra-Bentler) model chi-square was used to calculate *RMSEA*, *NNFI*, and *CFI.* The computation of these and other fit indices based on the *C3* chi-square are detailed in Appendix C.

Results indicated that the model improved. The CFA was run using the same second half of the full data (n = 920) set as the CFA that followed up the provisional EFA; however, the removal of the Cognitive Skills items resulted in slight modifications to distributional properties. As expected, the model still demonstrated significant multivariate skew (Z = 104.61, $p < .001$) and kurtosis (Z = 50.83, $p < .001$), albeit with slightly decreased Z-scores. Mardia's Index of Relative Multivariate Kurtosis was, at 1.51, below the Z-cutoff of 1.96 (for $\alpha = .05$, two-tailed distribution) (Mardia, 1970), but above the 1.5 cutoff to recommend use the *C3* model (Forero et al., 2009, p. 636). The condition number decreased from 16.40 to 15.56. This value is still above the optimal cutoff of 15 (but well below the upper cutoff of 30), which signify multicollinearity. All factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. Regression coefficients stabilized: low $R^2 = .48$; high $R^2 = .79$). It was concluded that the new model had an acceptable outcome. Table 12 summarizes item factor loadings and mean factor scores yielded from the 36-item, 6-function CFA. Table 13 lists the factor correlations. Per the *C3* (Satorra-Bentler) test statistic, $\chi^2(579) = 2475.18$, $p < .001$. As before, it is likely that the significant chi-square is due to the sample being overpowered, rather than an indication of poor fit. The *RMSEA* decreased from .067 to .059, indicating improvement in fit. *RMSEA* values $\leq .05$ indicate excellent fit; so although slightly outside of the optimal value, the RMSEA is much below the .08 cutoff that indicates adequate fit[5]. The χ^2/df ratio decreased from 4.75 to 4.28, still below the "adequate" cutoff of 5.0 (Byrnes, 1989, p. 55). The

[5] Note that with the *C4* χ^2 the *RMSEA* = .059. With the *C2*, which is the chi-square on which the LISREL default *RMSEA* is based, is.0581. The *C2* as discussed in a previous section is known to be biased with noncontinuous, nonnormal data. Although the *C2* yields an *RMSEA* value more advantageous to the model, it was disregarded in the current study. The *C4* chi-square, like the *C3*, also corrects for nonnormality, and sometimes with a benefit to the model. However, its use is controversial (as also discussed in a previous section); so the current study opted to report the *C3* results and the fit indices based upon it.

NNFI increased from .982 to .986, and the *CFI* increased from .983 to .987; both indicated excellent fit (optimal cutoff ≥ .95).

Other results suggested that the "overexplaining" issue had been resolved by the removal of the Cognitive Skills items. The SRMR, which reflects model error, dropped considerably, from .051 to .045, which was now below the optimal cutoff of .05 (Hu & Bentler, 1999, p. 24). The reduced error was reflected in the results of the standardized residuals analyses. The median standardized residual, although it switched signs, moved closer to the optimal value of 0, from .103 to −.066. Positive skewness remained, but decreased (residuals range from −3.91 to +11.02). The number of standardized residuals < −2.00 dropped from 22 (3%) to 15 (2%); likewise for residuals > +2.00, down from 55 (7%) to 34 (4%). The normal probability (Q) plot showed a greater adherence of residuals to follow the diagonal line. The break in pattern on the upper end of the plot, although less severe, remained. However, the break on the lower end of the residual plot disappeared. This is evidence that, although the known violations of normality remained, excess error was reduced, and unnecessary parameters removed (Raykov & Marcoulides, 2006, p. 33).

Structural equation modeling (SEM) reliability calculations for each of the six factors all exceeded the .70 cutoff to demonstrate high internal validity (Memon, 2012, p. 11): Conversation = .899; Perspective-Taking = .833; Relationship Maintenance = .937; Behavioral Control, Teaching, Problem Solving = .937; Emotion Regulation = .948; and Self = .892. The SEM reliability calculation are nearly identical to the ordinal reliability α reported in the 6-function EPAF.

Per the SEM average variance extraction calculations, the amount of variance accounted for by each function also exceeded the minimum recommended value of 50%: Conversation =

59.91%; Perspective-Taking = 71.43%; Relationship Maintenance = 65.09%; Behavioral Control, Teaching, Problem Solving = 62.33%; Emotion Regulation = 75.14%; and Self = 62.46%. All average factor variances decreases slightly after the removal of the Cognitive Skills items from the model. This supports the current study's contention that the Cognitive Skills items were speciously accounting for variance in the model (Cohen et al., 2004; Tabachnick & Fidell, 2007).

Hypothesis 1 Conclusion

Hypothesis 1 stated that the CRS-A, when administered to a diverse, college sample, would replicate the 7-function structure found in the original CRS sample. Neither the provisional EFA with follow-up CFA, nor the EPAF with follow-up CFA supported this prediction. Instead, evidence was found for a modified version of the CRS-A, a 6-function solution that omitted the CRS factor of Cognitive Skills. As the 6-function model was a better fit to the data by multiple criteria, validation of the 6-function model and the testing of Hypothesis 2 proceeded with a series of MGCFAs for test-retest, and gender and ethnicity invariance.

Hypothesis 2 Analyses

An SEM approach was used to examine both test-retest validity of the 6-function CRS-A, as well as its invariance across gender and ethnic groups. Incrementally constrained multigroup confirmatory factor analyses (MGCFA) were conducted and compared. Per the CFA procedure used to test Hypothesis 1, data were treated as ordinal, the method of estimation was RULS, and the model chi-square was the *C3* (Satorra-Bentler). Likewise, all goodness-of-fit and adequacy diagnostics per the previous CFA procedures were included.

Specifically, MGCFA tests the equality of groups' covariance matrices; i.e., whether or not the groups behave as one (Byrne, 1989, p. 126). If covariance matrices align, examining one group provides information about the other (Byrne, 1989, p. 126). If the covariance matrices do not align, that indicates that the instrument operates nonequivalently across groups (Byrne, 1989, p. 125). The latter suggests that results may necessitate an interpretation unique to that group.

Single-group analyses. Samples grouped on nonrandom characteristics like gender and ethnicity could yield models unique from the full-sample model (Byrne, 1989, p. 125). Therefore, single-group CFAs were conducted as a first step to demonstrate acceptable per-group fit before proceeding with multigroup analyses. Because the CRS-A is a new instrument for which no comparative empirical evidence or direct theory exists, all MGCFAs in the current study were exploratory in nature. As such, it was assumed that groups were essentially structurally identical at baseline. That is, incremental constraints across groups notwithstanding, no other structural accommodations to group models were made.

Multigroup analyses. If the single-group results were satisfactory, the following incrementally constrained MGCFAs were run in the following order: Configural (baseline), metric (structural/factor loading), scalar (intercept), error variance, factor variance, factor covariance, and factor means. The current study used the MGCFA protocol per Milfont & Fischer (2012), a summary of which is presented in Appendix F.

Evaluation of model comparisons. Once all single group models were evaluated for fit, a series of model comparisons were made based on the protocol outlined by Milfont and Fischer (2010). By convention, a nonsignificant change (Δ) in chi-square between two successively constrained models is considered evidence of invariance at the level of the more highly constrained model (Byrne, 1989). Given the size and complexity of the 6-function CRS-A model, two recommendations for accommodating chi-square sensitivity were adopted. One, the significance level for chi-square comparison were set at .01 rather than .05 (Raykov &

Marcoulides, 2006, p. 215). Two, practical model change for the *NNFI*, *CFI*, X χ^2/df, *RMSEA* was also evaluated. Changes in fit indices that did not surpass a tolerance threshold of .01 was considered support for model invariance (Chen, Sousa, & West, 2005).

Because the data in the current study were significantly MV nornnormal, the *C3* (Satorra-Bentler) model chi-square, which is "scaled," and thus corrects for MV nonnormality (Jöreskog, 2004), was used for evaluating structural fit. The *C3* chi-square is derived by dividing the *C1* (maximum likelihood) chi-square by a scaling factor that accounts for nonnormality (Byrne, 1995, p. 147; Satorra, 2000). Therefore, the *C3* chi-square is not distributed like a conventional chi-square, precluding its use in the conventional chi-square difference test used to evaluate invariance across nested multigroup models (Satorra, 2000). So before conducting chi-square difference tests with models based on the *C3* chi-square, the *C3* chi-square must undergo an adjustment to render it appropriate for model comparison.

The following is the formula used in the current study to adjust the C3 chi-square for use in nested MGCFA invariance testing:

$$\bar{T}_d = \frac{\chi^2_{C1_1} - \chi^2_{C1_0}}{\left(\frac{df_1\left(\frac{\chi^2_{C1_1}}{\chi^2_{C3_1}}\right) - df_0\left(\frac{\chi^2_{C1_0}}{\chi^2_{C3_0}}\right)}{\left(df_1 - df_0\right)} \right)}$$

Where *C1* = the maximum likelihood chi-square test statistic, and *C3* = the scaled Satorra-Bentler chi-square test statistics.

The following summarizes the current study's three MGCFA invariance tests.

Hypothesis 2a results: Test-retest. An MGCFA approach, as outlined by Munro (2005), was used to confirm the internal validity of the CRS-A 6-function model. A total of 192 cases from the winter semester featured SONA-assigned identifiers to indicate that those respondents had completed the CRS-A sometime during the preceding fall semester. Given the SONA semester cutoff periods, respondents' completion of the Retest component could have occurred any time between three and 18 weeks from Test. Respondent exact completion dates were not available. Also not available was information regarding which courses students were enrolled in available, so it is unknown what percentage of Retest respondents were course repeaters. Results of frequency analysis indicated that 81.25% (n = 156) of retest respondents were Female. Results of bivariate logistic regression analysis, using Retest (No = 1; Yes = 1) as the dependent variable and Gender (Male = 0; Female = 1) as the predictor, significantly predicted participation at Retest, b = .62, Wald = 10.37, p = .001. Females were 1.86 times more likely than Males to participate in Retest. In terms of ethnicity, results of logistic regression analyses indicated that participation in Retest was not predicted by any of the nine ethnic affiliations: Caucasian (44.3% of Retest sample; n = 85), b = .44, Wald = .40, p = .685; African-American/Black (20.8% of Retest sample; n = 40), b = –.17, Wald = .12, p = .728; Arab (14.1% of Retest sample, n = 27), b = –.41, Wald = .66, p = .415; Asian (9.9% of Retest sample, n = 19), b = –.19, Wald = .13, p = .715; Hispanic (1.6% of Retest sample, n = 3), b = –.16, Wald = .09, p = .762; Multiracial (3.1% of Retest sample, n = 6), b = –1.03 Wald = 1.82, p = .177; Native American (0.5% of Retest sample, n = 1), b = –.33, Wald = .27, p = .603; Hawaiian/Pacific Islander (0.5% of Retest sample, n = 1), b = .31, Wald = .07, p = .797; Other (2.6% of Retest sample, n = 5), b = .82, Wald = .43, p = .513; Decline to Answer (2.6% of Retest sample, n = 5), Wald = 6.54, p = .685.

Univariate datascreening in LISREL 9.1 (Scientific Software International, 2012) indicated that both the Test and Retest samples were negatively skewed and platykurtic. Multivariate normality diagnostics showed that Mardia's Index of Relative Multivariate Kurtosis was 1.36 for the Test group data and 1.39 for the Retest group data. Both groups' indices were below the Z-cutoff of 1.96 (for $\alpha = .05$, two-tailed distribution) (Mardia, 1970) to suggest that multivariate kurtosis was not so severe as to prohibit SEM analyses (Forero et al., 2009). Other datascreening diagnostics for Test indicated significant multivariate skew ($Z = 62.67$, $p < .001$) and kurtosis ($Z = 20.81$, $p < .001$), and likewise for Retest, ($Z = 64.16$, $p < .001$) and kurtosis ($Z = 21.34$, $p < .001$) The condition numbers for both groups were high (Test = 29.55, Retest = 28.21), but below the upper cutoff of 30 for both tests to indicate possible multicollinearity (Cohen et al., 2004). However, as with the CFA, the high value could also be due to the intercorrelating factors. Finally, values of indices and test statistics were equivalent across groups, suggesting that distributional properties of both groups were similar (Raykov & Marcoulides, 2006, p. 213).

CFA models 2a1 and 2a2: Single groups. Results of the single-group analyses indicated that the 6-function configuration held for both Test and Retest groups. Therefore, the current study proceeded with MGCFA invariance tests with Group 1 = Test (fall semester) and Group 2 = Retest (winter semester). Results of the CFAs were as follows. For Test: $\chi^2(579) = 1126.92$, $p < .001$, $RMSEA = .0704$, $\chi^2/df = 1.95$, $NNFI = .975$, and $CFI = .977$. For Retest: $\chi^2(579) =970.66$, $p < .001$, $RMSEA = .060$, $\chi^2/df = 1.68$, $NNFI = .987$, and $CFI = .988$. For the Test group, all factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. However, for Retest, three items in the theta-delta matrix had t-test values < 2.00 ($t < 2.00$: $t = 170$, $t = 120$). As discussed in a previous section, nonsignificant results in the theta-matrix are likely when samples are small. For both groups, $CN < 200$ (Test = 113.05; Retest = 131.09) indicates that the samples may not on their own be sufficient to determine model fit (Bollen & Lang, 1988; Hu & Bentler, 1995, p. 24). The more problematic issue is that *n. s.* theta matrix results can cause multigroup models to become "not positive definite," and possibly fail to converge (Hu & Bentler, 1995). However, if multigroup models run, *n. s.*, results in the theta matrix can be ignored (Hu & Bentler, 1995). As such, single group models were deemed appropriate for MGCFA.

Model 2b: Multigroup configural invariance. Model 2b investigated the configural invariance of the two groups (overall N = 384). The condition number of 29.53 was below the upper cutoff of 30, indicating the possibility of multicollinearity as discussed regarding the single group results.

Model 2b fit indices demonstrated excellent model fit at the configural level. Per the *C3* (Satorra-Bentler) test statistic, $\chi^2(1158) = 2247.97$, $p < .001$. As with previous CFAs, significant *C3* results are likely due to the overpowered sample. The *RMSEA* of .050 indicated excellent fit. The χ^2/df ratio of 1.94 also indicated excellent fit, where values ≤ 2 are preferred (Byrne, 1989, p. 55). The *NNFI* (.975) and *CFI* (.977) also indicated excellent fit. Therefore, results indicated that Model 2b was appropriate as a multigroup baseline model against which to compare incrementally constrained models. Conceptually, the CRS-A demonstrated configural integrity across time.

Model 2c: Multigroup metric invariance. Model 2c held factor loadings of Group 2 (Retest) equal to those of Group 1 (Test) to test structural invariance. The condition number held at 29.53. As expected, the Model 2c *C3* chi-square was again significant, $\chi^2(1188) = 2288.83$, $p < .001$. However, the difference in fit between structural model and the baseline (configural) model, after the *C3* adjustment described above, was not significant ($\overline{T}_d$ (30) < 1.00, p = 1.00), providing evidence that the CRS-A is structurally invariant across time. Other indices also showed model improvement within recommended tolerance levels[6] to also support structural invariance: *RMSEA* decreased to .049, the χ^2/df ratio decreased to 1.93, and the *NNFI* (.975) and *CFI* (.977) held. Table 14 summarizes the results of the Test-Retest difference tests.

Model 2d: Multigroup scalar invariance. Model 2d held both the factor loadings and intercepts of Group 2 (Retest) equal to those of Group 1 (Test) to test scalar invariance (overall N = 384). The condition number dropped to 14.69, below the optimal cutoff of 15. The *C3* chi-square was significant, $\chi^2(1218) = 3744.12$, $p < .001$. Likewise, the adjusted difference in fit between Model 2d and Model 2c was significant at the .01 level, ($\overline{T}_d$ (30) = 99.38, $p < .001$), indicating that the CRS-A is not scalar invariant across time. Conceptually, this suggests that respondents who have the same score on the latent factor (one of the six functions) would have a different observed score (on one of the function's corresponding items) depending on which semester the respondent completed the survey (Milfont & Fischer, 2010, p. 115). However, like the overall model chi-square test, the change in chi-square test is overly sensitive to models with a large number of constraints, so should be considered in conjunction with practical fit indices (Little, 1997, p. 58; Milfont & Fischer, 2012, p. 117). Fit index contrasts indicated that no change exceeded the .01 tolerance threshold: *RMSEA* decreased to .042, the χ^2/df ratio decreased to 1.67, the *NNFI* increased to .980, and the *CFI* increased to .981.

It is recommended in the literature that, once a significant chi-square difference has occurred between models, invariance testing stop (Byrne, 1989). Further, a lack of scalar invariance should prohibit the testing of factor mean invariance (Byrne, 1989). However, there is also wide recognition that the assumption of perfect model fit is problematic (Bentler & Bonnett, 1980; Little, 1997; Milfont & Fischer, 2012, p. 117), and that adequate practical fit can inform

[6] See previous description of cutoffs per index.

the determination of invariance (Little, 1997, p. 58). Therefore, the CRS-A was considered scalar invariant and invariance testing proceeded.

Model 2e: Multigroup error variance invariance. In this model, factor loadings, intercepts, and error variances were held constant across groups. The condition number held at 14.69, below the optimal cutoff of 15. The *C3* chi-square was significant, $\chi^2(1254) = 3744.12$, $p < .001$. However, the adjusted difference in fit between Model 2e and Model 2d was not significant at the .01 level, ($\overline{T}_d$ (36) < 1.00, $p = 1.0$). Results therefore indicated the CRS-A demonstrated error variance invariance across time. From a conceptual standpoint, this implies that the same degree of measurement error occurred regardless of whether the survey was completed in the fall or winter semester. The conclusion was supported by the improved model fit indicated by the other fit indices: *RMSEA* decreased to .040, the χ^2/df ratio decreased to 1.62, and the *NNFI* (.980) and *CFI* (.981) held.

Model 2f: Multigroup factor variance invariance. Model 2f held constant factor loadings, intercepts, error variances, and factor variances. The condition remained unchanged 14.69. The *C3* chi-square for model 2f was significant, $\chi^2(1260) = 3744.12$, $p < .001$. The adjusted difference in fit between Model 2e and Model 2f was not significant at the .01 level, ($\overline{T}_d$ (6) < 1.00, $p = 1.00$). As such, there is evidence that the CRS-A is factor variance invariant across time. That is, respondents' range of scores on the latent factors were equivalent regardless of which semester the CRS-A was completed. Results were corroborated with other indices, all of which remained the same between tests of Model 2e and Model 2f.

Model 2g: Multigroup factor covariance invariance. Model 2g constrained as equal factor loadings, intercepts, error variances, and factor variances. The condition number stayed at 14.69. The Model 2g *C3* chi-square was significant, $\chi^2(1275) = 3744.12$, $p < .001$, whereas the adjusted difference in fit between Model 2g and Model 2f, $\overline{T}_d$ (15) < 1.00, p = 1.00), was not significant at the .01 level. These results show that the CRS-A is invariant in terms of factor covariances, such that the same relation between latent factors exists regardless of semester. Other fit indices also showed invariance: *RMSEA* held at .040, the χ^2/df ratio decreased to 1.60, and the *NNFI* and *CFI* also held.

Model 2h: Multigroup factor mean invariance. Finally, Model 2h constrained factor loadings, intercepts, error variances, factor variances, factor covariances, and factor means of Group 2 (Retest) to equal to those of Group 1 (Test). The condition number increased back to 29.53, suggesting possible multicollinearity. The *C3* chi-square was significant, $\chi^2(1281)$ = 5131.63, p < .001. The adjusted difference in fit between Model 2h and Model 2g was not significant at the .01 level, $\overline{T}_d$ (6) =13.95, p = .030. As such, factor means were shown to be invariant across time. This suggests that respondents' understanding of each latent factor's underlying concept was consistent regardless of the semester in which the CRS-A was completed. Although some fit indices changed, all were within the .01 tolerance level to imply continued model fit: *RMSEA* = .044; χ^2/df ratio = 1.67; and *NNFI* and *CFI* each = .981. Of note, many sources recommend against accepting factor mean invariance when scalar invariance has been rejected (Byrne, 1989; van de Schoot, Lugtig, & Hox, 2012, p. 6). However, a lack of appreciable change in practical model fit recommended that scalar invariance, and thus factor mean invariance, in the test-retest context. Therefore, the current study concluded that the CRS-A demonstrated invariance over time.

Hypothesis 2b results: Gender. Because the male CRS-A sample (n = 529) was substantially smaller than the female sample (n = 1305), 529 CRS-A female cases were randomly selected for use in MGCFA invariance tests. Also, because the Male sample included all group cases, the Male group model was used as the basis of multigroup comparison.

Univariate datascreening in LISREL 9.1 (Scientific Software International, 2012) indicated that both the Male and Female samples were negatively skewed and platykurtic. Multivariate normality diagnostics showed that, for the Male group, Mardia's Index of Relative Multivariate Kurtosis was 1.47. As this is below the Z-cutoff of 1.96 (for α = .05, two-tailed distribution) (Mardia, 1970), SEM analyses should not be adversely affected by the sample's MV kurtosis (Forero et al., 2009). This was also the case for the Female group, which had a Mardia's index of 1.44. Other datascreening diagnostics for the Males group indicated significant MV skew (Z = 89.15, p < .001) and kurtosis (Z = 37.49, p < .001). The Female group also showed significant MV skew (Z = 83.93, p < .001) and kurtosis (Z = 36.79, p < .001). That the gender groups were significantly but not overly severely MV nonnormal supported the continued use of RULS estimation and the *C3* model chi-square.. The condition numbers for both groups were well below the optimal cutoff of 15 (Males = 11.49, Females = 11.87) to indicate no issues with multicollinearity (Cohen et al., 2004). That the values of all indices and test statistics in both groups indicate that, at least distributionally, the Male and Female groups were similar.

CFA models 3a and 3b: Single groups. Results of the single-group analyses indicated that the 6-function configuration held for both Male and Female groups. Therefore, the current study proceeded with MGCFAs using the Male group (Group 1) model as the basis of comparison for the Female group (Group 2) model. Results of the CFAs were as follows. For Males: $\chi^2(579)$ = 1592.79, p < .001, *RMSEA* = .058, χ^2/df = 2.75, *NNFI* = .987, and *CFI* = .988. For Females:

χ^2(579) = 1766.01, $p < .001$, *RMSEA* = .062, χ^2/df = 3.05, *NNFI* = .983, and *CFI* = .985. For both groups, all factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. Although the Hoelter's Critical N for the Male group was > 200 (*CN* = 220.15), it was just under the 200 cutoff for the Female group (*CN* = 198.65). This may indicate that the Female sample is not large enough to determine model fit (Bollen & Lang, 1988; Hu & Bentler, 1995, p. 24). Although more Female cases could have been randomly added to the sample to boost its *CN*, the distributions were otherwise similar, all matrix parameters were positive and significant, and the *CN* ultimately exceeded 200 in all MGCFAs. Therefore, it was decided that cases would not be added, and that the single group models were appropriate for MGCFA.

Model 3b: Multigroup configural invariance. Model 3b investigated the configural invariance of the Male and Female groups (overall *N* = 1058). The condition number of 15.87 was just over the optimal cutoff of 15, but well below the upper cutoff of 30, at which point multicollinearity can be an issue. Model 3b fit indices demonstrated excellent model fit at the configural level. Per the *C3* (Satorra-Bentler) test statistic, χ^2(1158) = 3182.56, $p < .001$. As with previous CFAs, significant *C3* results can be due to the sample being overpowered, so other fit indices must be considered. The *RMSEA* of .041 was below the optimal cutoff of ≤ .05 to indicate excellent fit. The χ^2/df ratio of 2.75 was slightly above the optimal cutoff of ≤ 2, but still considered adequate (Byrne, 1989, p. 55). The *NNFI* (.987) and *CFI* (.988) were well above the optimal cutoff of ≥ .95 (Byrne, 1989, p. 55). As such, results showed that Model 3b was an appropriate baseline for MGCFA. Conceptually, results indicated that the configural integrity of the CRS-A held across gender groups.

Model 3c: Multigroup metric invariance. Model 3c held factor loadings of Group 2

(Females) equal to those of Group 1 (Males) to test structural invariance (overall $N = 1058$). The condition number held at 15.87. As expected, the Model 3c *C3* chi-square was again significant, $\chi^2(1188) = 3241.63$, $p < .001$. As desired, the difference in fit between structural model and the baseline (configural) model, after the *C3* adjustment described in a previous section, was not significant, $\bar{T}_d$ (30) < 1.00, $p = 1.00$. Thus there was sufficient evidence that the CRS-A is structurally invariant across gender. Other indices also showed model improvement within recommended tolerance levels[7] to also support structural invariance: *RMSEA* decreased to .041, the χ^2/df ratio decreased slightly to 2.75, and the *NNFI* (.987) and *CFI* (.988) held. Table 15 summarizes the results of the Gender groups' difference tests.

Model 3d: Multigroup scalar invariance. Model 3d held both the factor loadings and intercepts of Group 2 (Females) equal to those of Group 1 (Males) to test scalar invariance (overall $N = 1058$). The condition number (12.00) dropped below the optimal cutoff of 15. The *C3* chi-square was significant, $\chi^2(1218) = 5803.42$, $p < .001$. Likewise, the adjusted difference in fit between Model 3d and Model 3c was significant, $\bar{T}_d$ (30) = 76.27, $p < .001$. This indicates that group intercepts are not equivalent across gender. Conceptually, this suggests that males and females who have the same score on the latent factor would not have the same observed scores (Milfont & Fischer, 2010, p. 115). However, as previously discussed, the high number of constraints and large sample size could be driving significance (Little, 1997, p. 58). Therefore, practical fit indices were examined. All though some indices showed a lack of model improvement, no change surpassed the .01 tolerance level: *RMSEA* increased to 041; the χ^2/df ratio also increased slightly to 2.77; and the *NNFI* and *CFI* each dropped .002 to .985. Therefore, the current study concluded that the CRS-A was scalar invariant across gender.

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[7] See previous description of cutoffs per index.

Model 3e: Multigroup error variance invariance. In this model, factor loadings, intercepts, and error variances were held constant across groups (overall N = 1058). The condition number held at 12.00, below the optimal cutoff of 15. The *C3* chi-square was significant, $\chi^2(1254) = 3359.36$, $p < .001$. The adjusted difference in fit between Model 3e and Model 3d was not significant, $\bar{T}_d$ (36) < 1.00, p = 1.0, to indicate that CRS-A is error variance invariant across gender. This suggests that the same degree of measurement error occurred regardless of whether the survey was completed by males or females. This conclusion was supported by the improved model fit indicated by the other fit indices: *RMSEA* decreased to .040, the χ^2/df ratio decreased to 2.68, and the *NNFI* and *CFI* both increased to .981.

Model 3f: Multigroup factor variance invariance. Model 3f held constant factor loadings, intercepts, error variances, and factor variances (overall N = 1058). The condition remained unchanged 12.00. The *C3* chi-square for model 3f was significant, $\chi^2(1260) = 3366.91$, $p < .001$. The adjusted difference in fit between Model 3e and Model 3f however was not significant ($\bar{T}_d$ (6) < 1.00, p = 1.00), to provide evidence that the CRS-A is factor variance invariant across gender such that respondents' range of scores on the latent factors were equivalent regardless of whether the respondent was male or female. Results were corroborated with other indices (*RMSEA*, χ^2/df, *NNFI*, *CFI*) remained unchanged from Model 3e and Model 3f.

Model 3g: Multigroup factor covariance invariance. Model 3g constrained as equal factor loadings, intercepts, error variances, and factor variances (overall N = 1058). The condition number stayed at 12.00. The Model 3g *C3* chi-square was significant, $\chi^2(1275) = 3371.27$, $p < .001$. The adjusted difference in fit between Model 3g and Model 2f was not significant, $\bar{T}_d$ (15) < 1.00, p = 1.00. These results suggest factor covariance invariance of the CRS-A. That is, the same relation between latent factors exists regardless of whether the respondent was male or female. Other fit indices also showed invariance: *RMSEA* decreased to .039, the χ^2/df ratio decreased to 2.64, and the *NNFI* and *CFI* held at .986.

Model 3h: Multigroup factor mean invariance. Finally, Model 3h constrained factor loadings, intercepts, error variances, factor variances, factor covariances, and factor means of Group 2 (Females) to equal to those of Group 1 (Males). The condition number (15.87) again surpassed the optimal cutoff to suggest the possibility of multicollinearity. The *C3* chi-square was significant, $\chi^2(1281) = 3118.59$, $p < .001$. The adjusted difference in fit between Model 3h and Model 3g was not significant, $\bar{T}_d$ (6) =10.82, $p = .094$. Results indicate therefore that factor means are invariant across gender. This suggests that females' understanding of the concept underlying each latent factor was consistent with that of males' understanding. Other fit indices reflected excellent fit to support factor mean invariance: *RMSEA* decreased to .037, the χ^2/df ratio decreased to 2.43, and the *NNFI* and *CFI* each increased to .989. As such, the current study concluded that the CRS-A was invariant across gender.

Hypothesis 2c results: Ethnicity. As was done with the Gender invariance data, a random sample of 451 cases was drawn from the Caucasian ethnic group so as to equal the African-American/Black (AAB) ethnic group sample (n = 451). Because of the CRS-A configural complexity, only the Caucasian and AAB groups were ultimately sufficiently large enough to successfully run MGCFAs. Although the AAB sample featured all cases for its group, the following ethnic invariance tests were based on the model for the Caucasian group. To treat the Caucasian group model as the basis for multigroup comparison was feasible given that previous validation studies of AM functions scales used primarily Caucasian samples (Bluck et al., 2005; Bluck & Alea, 2011; Kulkofsky & Koh, 2009; Robitaille et al., 2010; Webster, 1997).

As such, comparing the AAB group models against the Caucasian group models afforded a greater degree of generalizability to results.

As was the case for all group samples, both the Caucasian and AAB groups were univariate negatively skewed and platykurtic. Multivariate normality diagnostics showed that Mardia's Index of Relative Multivariate Kurtosis for both groups was below the 1.96 Z-cutoff (Caucasian = 1.41, AAB = 1.44). Per this diagnostic, MV kurtosis is tolerable and SEM analyses can proceed (Forero et al., 2009). However, datascreening results for the Caucasian group showed significant MV skew (Z = 78.12, p < .001) and MV kurtosis (Z = 33.18, p < .001). Results for the AAB group also showed significant MV skew (Z =77.85, p < .001) and kurtosis (Z = 33.92, p < .001). As with the CFA models and previous MGCFA models, the significant, but not overly severe, MV nonnormality supported the continued use of RULS estimation and the *C3* chi-square. The condition numbers for both groups were below the optimal cutoff of 15 (Caucasian =10.93, AAB = 13.00) to indicate no issues with multicollinearity (Cohen et al., 2004). All results suggested distributional equivalency across groups.

CFA models 4a and 4b: Single groups. Results of the single-group analyses indicated that the 6-function configuration held for both the Caucasian and AAB groups. Therefore, the current study proceeded with MGCFA invariance tests with Group 1 = Caucasian, and Group 2 = AAB. Results of the CFAs were as follows. For the Caucasian group: $\chi^2(579)$ = 1631.77, p < .001, *RMSEA* = .064, χ^2/df = 2.82, *NNFI* = .981, and *CFI* = .983. For the AAB group: $\chi^2(579)$ = 3323.01, p < .001, *RMSEA* = .064, χ^2/df = 2.82, *NNFI* = .986, and *CFI* = .987. For both groups, all factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. As such, single group models were deemed appropriate for MGCFA.

Model 4b: Multigroup configural invariance. Model 4b investigated the configural invariance of the two groups (overall N = 902). The condition number of 14.90 was below the optimal cutoff of 15 to suggest no issues with multicollinearity. Model 4b fit indices demonstrated excellent model fit at the configural level. Per the *C3* (Satorra-Bentler) test statistic, $\chi^2(1158) = 3259.91$, $p < .001$. The significant *C3* results were likely being driven by the overpowered sample, so other fit indices were considered. The *RMSEA* of .045 indicated excellent fit. The χ^2/df ratio of 2.82 indicated adequate fit, as it was just over the optimal ≤ 2.0 cutoff (Byrne, 1989, p. 55). The *NNFI* (.981) and *CFI* (.983) also indicated excellent fit. Therefore, results indicated that Model 4b was appropriate as a multigroup baseline model against which to compare incrementally constrained models. Conceptually, the CRS-A demonstrated configural integrity across time.

Model 4c: Multigroup metric invariance. Model 4c held factor loadings of Group 2 (AAB) equal to those of Group 1 (Caucasian) to test structural invariance (overall N = 902). The condition number held at 14.90. The Model 4c *C3* chi-square was, given the sample size, significant as expected, $\chi^2(1188) = 3318.08$, $p < .001$. However, the difference in fit between structural model and the baseline (configural) model, after the *C3* adjustment described above, was not significant ($\bar{T}_d$ (30) < 1.00, p = 1.00). The latter was evidence that the CRS-A is structurally invariant across ethnic groups. Other indices corroborated ethnic-group configural invariance: *RMSEA* held at .045, the χ^2/df ratio decreased to 2.79, and the *NNFI* (.982) and *CFI* (.983) each held. Table 16 summarizes the results of the ethnicity chi-square difference tests.

Model 4d: Multigroup scalar invariance. Model 4d held both the factor loadings and intercepts of Group 2 (AAB) equal to those of Group 1 (Caucasian) to test scalar invariance. The condition number dropped further below the optimal 15 cutoff to 10.90. The *C3* chi-square was significant, $\chi^2(1218) = 3333.49$, $p < .001$, as was the adjusted difference in fit between Model 4d and Model 4c, ($\overline{T}_d$ (30) = 90.38, $p < .001$). Results therefore indicated that the CRS-A is not scalar invariant across ethnic groups. That is, AAB and Caucasian respondents who have the same score on the latent factor have different scores on items (Milfont & Fischer, 2010, p. 115). However, practical fit indices were evaluated given the chi-square's sensitivity to large number of constraints and large sample sizes (Little, 1997, p. 58). The scalar invariant model showed modest improvement over the structural invariant model with no appreciable change in practical fit at the .01 tolerance level. Both the *RMSEA* (.044) and the χ^2/df ratio (2.74) decreased. The *NNFI* (.980) and CFI (.981) both dropped, but well within the .01 tolerance limit. Scalar invariance was therefore accepted.

Model 4e: Multigroup error variance invariance. In this model, factor loadings, intercepts, and error variances were held constant across groups. The condition number, at 10.90, did not change. The *C3* chi-square was significant, $\chi^2(1254) = 3321.54$, $p < .001$. The adjusted difference in fit between Model 4e and Model 4d was not significant ($\overline{T}_d$ (36) < 1.00, $p = 1.0$) to suggest that the CRS-A was error variance invariant with respect to ethnicity. Conceptually, the same degree of measurement error that occurred in the Caucasian group model occurred in the AAB group model. This conclusion was supported by an improvement in *RMSEA*, which decreased to .043; the χ^2/df ratio decreased to 2.65; and increase in both the *NNFI* and *CFI* to .981 each.

Model 4f: Multigroup factor variance invariance. Model 4f held constant factor loadings, intercepts, error variances, and factor variances. The condition number remained unchanged 10.90. The *C3* chi-square for model 2f was significant, $\chi^2(1260) = 3328.73$, $p < .001$. The adjusted difference in fit between Model 4e and Model 4f was not significant ($\overline{T}_d$ (6) < 1.00, p =

1.00), to suggest that the CRS-A is factor variance invariant across ethnic groups. That is, the range of scores on the latent factors for the AAB group was not significantly different from the range of latent scores on latent factors for the Caucasian group. Other fit indices also remained unchanged.

Model 4g: Multigroup factor covariance invariance. Model 4g constrained as equal factor loadings, intercepts, error variances, and factor variances. The condition number held at 10.90. The Model 4g *C3* chi-square was significant, $\chi^2(1275) = 3333.02$, $p < .001$, as was the adjusted difference, $\bar{T}_d$ (15) < 1.00, $p = 1.00$). That the change was nonsignificant indicates that the CRS-A is invariant in terms of factor covariances. That is, the same relation between latent factors exists for both the Caucasian and AAB groups. Other fit indices also showed invariance: *RMSEA* decreased to .042, the χ^2/df ratio decreased to 2.61, and the *NNFI* and *CFI* also held at .981 each.

Model 4h: Multigroup factor mean invariance. Lastly, Model 4h constrained factor loadings, intercepts, error variances, factor variances, factor covariances, and factor means of Group 2 (AAB) to equal to those of Group 1 (Caucasian). The condition number increased to 14.90, but was still below the optimal multicollinearity cutoff of 15. The *C3* chi-square was significant, $\chi^2(1281) = 3191.56$, $p < .001$. However, the adjusted difference in fit between Model 4h and Model 4g was not significant at the .01 significance level, $\bar{T}_d$ (6) =12.84, $p = .046$. Results suggest that the AAB group understood the concept of each underlying latent factor consistent with that of the Caucasian group. Practical fit indices indicated model improvement within the .01 tolerance threshold. The *RMSEA* decreased to.041, the χ^2/df ratio decreased to 2.49, the *NNFI* increased to .985, and the *CFI* increased to .984. Therefore, factor mean invariance was accepted. The CRS-A was found in the current study to be invariant across ethnic groups.

Hypothesis 2 Conclusion

Hypothesis 2 originally predicted test-retest internal validity and invariance with gender and ethnic group with the invariance with a 7-function CRS-A model. However, that model proved untenable, so Hypothesis 2 analyses proceeded by invariance testing the 6-function CRS-A. Results showed the CRS-A to be invariant across time, gender, and ethnicity.

Hypothesis 3 Analyses

Hypothesis 3 predicted that the CRS-A would map onto the three theoretical dimensions (Self, Social, Directive) of the TALE (Bluck et al., 2005; Bluck & Alea, 2011) when tested with multitrait-multimethod (MTMM) CFA analyses. Further, it was hypothesized that comparisons of the CRS-A to the TALE would yield evidence of construct validity; i.e., how well the instrument measures the construct it was designed to measure (Bryant, 2000, p. 138). A program of multitrait-multimethod (MTMM) CFAs designed to test the specific components of construct validity were run using the full dataset ($N = 1841$).

Using an MTMM protocol outlined by Byrne (2013), the current study conducted a series of CFAs using LISREL 9.1 (Scientific Software International, 2012). All MTMM CFAs were based on a 3 × 2[8] MTMM matrix comprised of three traits (Social, Directive, Self) and two methods (CRS-A and TALE). The current study assessed CRS-A construct validity using the

[8] Although MTMM analyses technically necessitate only a 2 × 2 (two traits, two methods) design when samples are ≥ 250 (Marsh & Grayson, 1995, p. 177), it is widely recommended that the minimum MTMM matrix be a 3 × 3 (three traits, three methods), even if samples are ≥ 250 (Brannick & Spector, 1990). Others yet have contended that, even with large samples, models featuring fewer than four traits and three methods can yield convergence problems, improper solutions, and/or specious parameter estimates (Brannick & Spector, 1990, pp. 330–331; Marsh & Grayson, 1995, p. 187). Although these concerns were known, and although a third method for measuring AM functions, the Reminiscence Functions Scale (Robitaille et al., 2010), was available, space limitations on the SONA prescreen precluded the addition of items from a third method. The literature's concerns as to the feasibility of the 3 × 2 matrix used in the current study were noted, the full $N = 1841$ dataset was used to help offset issues, and MTMM results interpreted accordingly.

TALE (Bluck & Alea, 2010). The TALE was found suitable for construct validation analysis of the CRS-A for the following reasons: (1) Kulkofsky and Koh found that all three TALE functions were significantly correlated with six of the seven functions of their validated version of the CRS (2009, p. 465)[9]. Table 17 summarizes the correlations between the TALE functions and validated CRS functions per Kulkofsky and Koh (2009, p. 465). This implied that the CRS-A should likewise be correlated with the TALE; (2) regression analysis in the current study showed that all three TALE functions significantly predicted five of the six CRS-A functions[10]; (3) the current study found that all three TALE functions uniquely predicted those CRS-A functions in a pattern aligned with theory. For example, the TALE function of Self was significantly correlated with the CRS-A function of Perspective-Taking (r = .303, p = .009). Likewise, the TALE function of Social was significantly correlated with the CRS-A function of Perspective-Taking (r = .48, p < .001). However, because Perspective-Taking is theoretically aligned with the TALE Social function, the finding that the TALE Social function uniquely predicts more of the variance in Perspective-Taking (r^2 = 8.9%) than does the TALE Self function (< 0.3%) suggests that the TALE is suitable for evaluating convergent and divergent validity. Table 18 summarizes the correlations and unique variance accounted for between TALE functions and the six CRS-A functions. Therefore, the current study configured CRS-A for MTMM analyses such that the CRS-A Self function mapped onto the TALE Self function; the CRS-A Conversation, Perspective-Taking, and Relationship Maintenance functions mapped onto the TALE Social function; and the CRS-A Behavioral Control/Teaching/Problem Solving and Emotion Regulation functions mapped onto the TALE Directive function.

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[9] The exception was the TALE Social function, which was not significantly correlated with the CRS Directive function, r = .08, p > .05.
[10] The exception was the TALE Self function, which was not significantly correlated with the CRS-A Conversation function, r = .27, p = .067.

For construct validity testing, MTMM CFA models are generally configured such that each item of all scales loads onto exactly one trait and exactly one method (Marsh & Grayson, 1995, p. 181). These loadings occur simultaneously in some models, or are omitted in other models (Marsh & Grayson, 1995). In the current study, each item of the CRS-A and TALE loaded onto one of the Social, Directive, or Self factors per their validated scale structures. All MTMM CFA models in the current study were run on correlation matrices based on polychoric (ordinal-level) correlations (Byrne, 1989, p. 105).

Similar to the chi-square difference tests performed on MGCGA models, evidence for construct validity can be found via contrasts between various MTMM models. Per the protocol outlined by Byrne (2013), four nested and differentially restricted MTMM models (Correlated Traits/Correlated Methods, No Traits/Correlated Methods, Perfectly Correlated Traits/Correlated Methods, and Correlated Traits/Uncorrelated Methods) were constructed and analyzed using LISREL 9.1 (Scientific Software, International, 2012). As was the case with the MGCFAs, all MTMM models used the *C3* model chi-square test statistic to correct for nonnormality. As such, before performing model-to-model comparisons, all *C3* chi-square values were adjusted per the formula described previously in the MGCFA section.

Hypothesis 3 analyses began with assessments of the CRS-A and TALE as single model CFAs. Next, model fit was evaluated for each of the four MTMM CFAs. Finally, MTMM models were compared per the protocol outlined by Byrne (2013) to establish CRS-A construct validity.

Model 5a1: CRS-A. Because the current study sought evidence of the CRS-A's construct validity via MTMM analyses with the TALE (Bluck & Alea, 2010), a CRS-A CFA using the three theoretical factors of Social, Directive, and Social was conducted on the entire dataset (N = 1841). The full dataset was used rather than either the EFA or CFA dataset alone for three reasons: (1) the CFA confirmed that the EFA and CFA samples were equivalent; (2) TALE data for all 1841 cases were available; and (3) given the instability of CFA MTMM solutions, the higher the sample size, the better, especially when working with a MTMM matrix smaller than 3 × 3 (Marsh & Grayson, 1995, pp. 186–187). Figure 8 illustrates the relation of the conceptual CRS-A model and its relation to the TALE's three theoretical functions. Univariate datascreening indicated that, as expected, CRS-A response data were negatively skewed and platykurtic. Multivariate normality diagnostics showed that Mardia's Index of Relative Multivariate Kurtosis was, at 1.56, below the Z-cutoff of 1.96 (for α = .05, two-tailed distribution) (Mardia, 1970); however, it was above the 1.5 cutoff to recommend an estimation methods and model chi-square that deals with multivariate nonnormality (Forero et al., 2009, p. 636). Other datascreening diagnostics indicated significant multivariate skew (Z = 120.92, p < .001) and kurtosis (Z = 73.87, p < .001). That the condition number of 10.58 was below the cutoff of 15 (Cohen et al., 2004, p. 424), indicated no issues with multicollinearity.

Results of the single-group analyses both showed adequate model fit. The model chi-square, as expected due to the large sample size, was significant, $\chi^2(591) = 7129.62$, $p < .001$, $RMSEA$ = .078, χ^2/df = 12.06, $NNFI$ = .975, and CFI = .967. All factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. Regression coefficients were somewhat unstable (low R^2 = .27; high R^2 = .74), signifying inconsistent reliabilities across items, and thus the model.

That this model fits ostensibly worse than the CFA run to validate the EPAF is likely due to assumption that the mapping of CRS items onto the TALE (Bluck et al., 2005; Bluck & Alea, 2011) would be replicated by the CRS-A. As discussed previously, the CRS-A was adapted from the Kulkofsky and Koh (2009, p. 460) theoretical model, which did not undergo any statistical testing for its association with the TALE. As such, correlations between the theoretical CRS items and the Social, Directive, and Self functions may be weaker or differently patterned than hypothesized but not actually calculated by Kulkofsky and Koh. As for the model linking CRS-A items to the three theoretical functions, no results strongly suggested a specific configural issue. All factor loadings were between .50–.80, suggesting model stability and proper affiliation. The *SRMR* = .066, which is below the optimal cutoff of .08 (Hu & Bentler, 1999), indicates a reasonable amount of model error. Based on the finding of an adequate model, it was concluded that the theoretical CRS model does not necessarily map onto the Social, Directive, and Self functions as proposed by Kulkofksy and Koh (2009).

Model 5a2: TALE. Analyses proceeded with a CFA of the 15-item TALE (Bluck & Alea, 2010), which also used the entire dataset ($N = 1841$). Table 5 summarizes TALE items and their associated theoretical AM function. The recoded TALE scores were again employed.

Univariate datascreening indicated that, as expected, TALE response data were negatively skewed and platykurtic. Multivariate normality diagnostics showed that Mardia's Index of Relative Multivariate Kurtosis was, at 1.31, below both the *Z*-cutoff of 1.96 (for $\alpha = .05$, two-tailed distribution) (Mardia, 1970), and the 1.5 cutoff that recommends an estimation methods and model chi-square that deals with multivariate nonnormality (Forero et al., 2009, p. 636). However, other datascreening diagnostics indicated significant multivariate skew ($Z = 40.70$, $p < .001$) and kurtosis ($Z = 36.40$, $p < .001$). The condition number, at 7.06, was well below the cutoff of 15 (Cohen et al., 2004, p. 424) to imply no issues with multicollinearity.

Results of the TALE single-group analyses showed adequate to poor model fit. The model chi-square, as expected due to the large sample size, was significant, $\chi^2(87) = 1557.26$, $p <$

.001. The weakness of the fit is indicated by the *RMSEA* = .096, χ^2/df = 17.90, *NNFI* = .964, and *CFI* = .967. All factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were significant and positive. Regression coefficients were stable (low R^2 = .47; high R^2 = .76), signifying good reliability across items, and thus the model.

Why this model did not demonstrate better fit is not clearly evident. The 15-item TALE was validated for use with adults (Bluck & Alea, 2011, p. 480). Differences in the distributional properties of the samples used for the TALE versus that used for the CRS-A may be a factor. As reported by Bluck and Alea (2011), the data used to validate the 15-item TALE were only slightly negatively skewed and not significantly so; thus variables were treated as continuous, and PPM with ML estimation was used (pp. 475–476). However, to verify that the poor fit was not due to the rescaling of the items, a CFA with the identical model was run with the exception that rating categories were left at their original values. Although values changed, the overall model fit did not. Thus it was concluded that there is only weak evidence for replication of the link between TALE functions and the 15 items with the current study data. However, MTMM analyses proceeded and results were interpreted with caution.

Model 5b: Correlated Traits/Correlated Methods (CTCM). The Correlated Traits/Correlated Methods (CTCM) model is the baseline model against which subsequent nested models featuring incrementally constrained or omitted parameters are compared (Byrne, 2013, p. 287). Configurally, the CTCM model allows all methods to intercorrelate, and all traits to intercorrelate, but does not allow methods and traits to intercorrelate (Byrne, 2013, p. 288). To construct the CTCM model in the current study, method factors (CRS-A and TALE) were allowed to correlate, as were trait factors (Social, Directive, and Self). Scale was set at 1.0 in the diagonal of the phi matrix (Byrne, 2013, p. 289). Figure 9 illustrates the current study's CTCM conceptual model.

Results of the single-model CTCM CFA indicated adequate to good model fit. The model chi-square, as expected due to the large sample size, was significant, $\chi^2(1169) = 9762.41$, $p < .001$. The results for the other fit statistics were mixed in their support of the model: $RMSEA = .063$, $\chi^2/df = 8.35$, $NNFI = .978$, and $CFI = .980$. Not all loadings were significant in the lambda (factor loading) and phi (unattenuated factor correlations) matrices with respect to Traits. However, this is not an uncommon occurrence in CTCM models, especially when models include fewer than four traits and three methods (Marsh & Grayson, 1995, p. 186), as is the case with the current study. Given the strictly technical nature of this problem (that each item must load on both a trait and a method factor), if the model converges, it is often considered acceptable to proceed (Byrne, 2013, p. 292), especially if sample size is sufficient (Marsh & Grayson, 1995, 186). In other results, the condition number, at 13.56, was below the cutoff of 15 (Cohen et al., 2004, p. 424) to imply no issues with multicollinearity. Regression coefficients were fairly stable for the CRS-A (low $R^2 = .42$; high $R^2 = .79$), but less so for the TALE (low $R^2 = .23$; high $R^2 = .72$). This suggests that reliabilities for the CRS-A were consistent with those of previous CFAs. TALE values were consistent with coefficients reported by Bluck and Alea (2011), which ranged from .47 ($R^2 = .23$) to .85 ($R^2 = .72$). A summary of CTCM fit results can be found in Table 19.

Model 5c: No Traits/Correlated Methods (NTCM). The No Traits/Correlated Methods (NTCM) model features correlations between items and their methods while excluding trait factors entirely (Byrne, 2013, p. 293). The NTCM model is configurally identical to the CTCM with the exception that trait factors have been omitted. Thus, the larger the discrepancy between the NTCM model and CTCM model, the greater the degree of intercorrelation between items of the same trait (Byrne, 2013, p. 297). Thus, when the model discrepancy between NTCM and CTCM is large and significant, the contrast is evidence of convergent validity (Byrne, 2013, p. 297). To construct the NTCM model in the current study, method factors (CRS-A and TALE) were included in the model and allowed to correlate, but trait factors (Social, Directive, and Self) were removed. Scale remained set at 1.0 in the diagonal of the phi matrix (Byrne, 2013, p. 289), which now included only the CRS and TALE factors. Figure 10 illustrates the current study's NTCM conceptual model.

Results of the single-model NTCM CFA indicated adequate model fit. The model chi-square, as expected due to the large sample size, was significant, $\chi^2(1224) = 16622.60$, $p < .001$. Evidence for adequate model fit is found in the following: $RMSEA = .083$, $\chi^2/df = 13.58$, $NNFI = .962$, and $CFI = .963$. It is not unusual for the NTCM model to demonstrate poorer fit than subsequent nested models, especially when the model features less than three methods (Byrne, 2013, p. 294; Marsh & Grayson, 1995, p. 187). Loadings in lambda, phi, and theta-delta matrices were all significant, which is expected with large samples and when factors are not loading onto more than one factor (Byrne, 2013; Marsh & Grayson, 1995). The condition number (13.56), below the cutoff of 15 (Cohen et al., 2004, p. 424), indicated no issues with multicollinearity. Fit results for the NTCM can be found in Table 19.

Model 5d: Perfectly Correlated Traits Correlated Methods (PCTCM). The PCTCM model is identical to the CTCM model with one exception: Whereas correlations between trait factors in the CTCM are free to vary, correlations between trait factors in the PCTCM are set to 1.0 in order to reflect "perfect" correlation (Byrne, 2013, p. 294). A discrepancy between the CTCM and PCTCM models thus indicates how far from "perfect" trait correlations are (Byrne, 2013). Thus the greater the discrepancy, the greater the extent to which dissimilar traits are not correlated, which, when substantial and significant, provides evidence of discriminant validity (Byrne, 2013, p. 300). To construct the PCTCM model in the current study, the configuration used in the CTCM was modified such that correlations between Social and Directive, Social and Self, and Directive and Self were set to 1.0 (Byrne, 2013, p. 289). Figure 11 illustrates the current study's PCTCU conceptual model.

Results of the PCTCM model indicated adequate fit. The model chi-square, as expected due to the large sample size, was significant, $\chi^2(1172) = 12746.86$, $p < .001$, the *RMSEA* = .073, $\chi^2/df = 10.88$, *NNFI* = .970, and *CFI* = .963. The comparison of the CTCM and PCTCM is reported below. Loadings in phi and theta-delta matrices were significant; however, some lambda loadings were not significant, which, as with previous models, can occur with MTMM models that necessitate items to load on both a trait and a method factor, but have fewer than four traits and three methods onto which those items can load (Byrne, 2013, p. 294; Marsh & Grayson, 1995, p. 187). The condition number (13.56) remained below the cutoff of 15 (Cohen et al., 2004, p. 424) to indicate no issues with multicollinearity. PCTCM fit results can be found in Table 19.

Model 5e: Correlated Traits/Uncorrelated Methods (CTUM). The Correlated Traits/Uncorrelated Methods (CTUM) model is the same as the CTCM model without method correlations (Byrne, 2013, p. 295). A discrepancy between the CTCM and CTUM models indicates a difference in models due to method effects (Byrne, 2013, p. 301)[11]. Method effects

[11] Another popular MTMM matrix model, the Correlated Traits/Correlated Uniqueness (CTCU) model, can be used to tease apart the systematic method bias from unreliability that are confounded in the CTUM model (Byrne, 2013, p. 304). However, a requirement to incorporating the CTCU matrix is that the number of traits be > 3 (Byrne, 2013, p. 304). When the number of traits = 3, which is the case in the current study, the CTCU cannot provide information beyond

are a type of discriminant validity in which correlations between items and factors are influenced by (i.e., not independent of) methods (Bryant, 2000, p. 121). To construct the CTUM model in the current study, the configuration used in the CTCM was modified such that the correlation between CRS-A and TALE factors was removed (Byrne, 2013, p. 298). Figure 12 illustrates the current study's CTUM model.

Results of the CTUM model indicated adequate model fit. The model chi-square, as expected due to the large sample size, was significant, $\chi^2(1170) = 10020.01$, $p < .001$, $RMSEA$ = .064, χ^2/df = 8.56, $NNFI$ = .977, and CFI = .979. Again, good model fit is unlikely with fewer than four traits and three methods (Marsh & Grayson, 1995, p. 187). Likewise, it is not unusual for factor loadings to be nonsignificant (Marsh & Grayson, 1995). In this case not all loadings in the lambda matrix for the CRS factor were significant, but all other loadings in all other matrices were significant. The condition number remained at 13.56, which was below the cutoff of 15 (Cohen et al., 2004, p. 424), to indicate no issues with multicollinearity in the CTUM model. Table 19 lists CTUM fit results.

Contrast Tests to Determine Construct Validity

The following sections detail results of the contrast tests performed to determine convergent and discriminant validity. Results of the assessment of method bias, which is an extension of discriminant validity, is also included. For all comparisons, a significant change in adjusted chi-square was evidence of construct validity. Additionally, the *CFI*, a practical fit index, was also assessed for significant change based on absolute $\Delta \geq .01$ (Cheung & Rensvold, 2002) This is because the change in chi-square (whether adjusted for not) is sensitive to sample size and violations of normality, so can be misleading if other fit indices are not also considered

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that provided with the CTUM model (Byrne, 2013, p. 304). Therefore, the CTCU model was not used in the current study.

(Byrne, 2013, p. 298). The ΔCFI was found to be highly appropriate in MTMM contrast tests compared to other change in fit indices (Cheung & Rensvold, 2002 per Byrne, 2013, p. 300). However, given that the MTMM model used in the current study was smaller than the recommended minimum MTMM model of four traits, and three methods, additional fit indices were evaluated for change to better substantiate conclusions. A summary of the relevant fit results for all contrast tests can be found in Table 20.

Convergent validity. Convergent validity is the degree to which (in terms of coefficient magnitude and statistical significance) items of a single trait are correlated (Byrne, 2013, p. 297). Conceptually, an instrument demonstrates convergent validity if the different methods by which one trait is measured intercorrelate strongly (Bryant, 2000, p. 120). For example, CRS-A items that indicate the Social function should be highly correlated with TALE items that indicate the Social function. It is assessed in the MTMM CFA framework by comparing the two nested models, the CTCM and the NTCM (Byrne, 2013, p. 297). A significant change in model chi-square is evidence of convergent validity (Byrne, 2013, p. 298).

The adjusted difference in fit between the CTCM (baseline) model and the NTCM model was significant, $\overline{T}_d$ (36) = 226.00, $p < .001$. Per the Byrne (2013) MTMM protocol, a significant difference is indicative of convergent validity. Comparisons of the following indices also supported convergent validity, as all met or exceeded the .01 tolerance level: $\Delta RMSEA = .01$; $\Delta NNFI = -.01$; and $\Delta CFI = -.02$. Additionally, the chi-square to degrees of freedom ratio increased by $\Delta\chi^2/df = 2.53$ to indicate that the CTCM and NTCM models are not equivalent.

Discriminant validity. Discriminant validity is the degree to which (in terms of coefficient magnitude and statistical significance) items of a single trait are not correlated (Byrne, 2013, p. 300). Conceptually, discriminant validity reflects whether scores on one item are unrelated to the scores of items underlain by a different factor (Bryant, 2000, p. 139). Discriminant validity is assessed in the MTMM CFA framework by comparing the CTCM (baseline) and the PCTCM (Byrne, 2013, p. 300). A significant change in model chi-square is evidence of discriminant trait validity (Byrne, 2013, p. 300).

The adjusted difference in fit between the CTCM (baseline) model and the PCTCM model was significant, $\overline{T}_d$ (82) = 627.54, p < .001. Per the Byrne (2013) MTMM protocol, a significant difference is indicative of discriminant validity with respect to traits. Comparisons of the following indices also supported discriminant validity in the first comparison set, as all met or exceeded the .01 tolerance level: $\Delta RMSEA$ = .02; $\Delta NNFI$ =–.02; and ΔCFI = –.02. Additionally, the chi-square to degrees of freedom ratio increased by $\Delta\chi^2/df$ = 5.23 to indicate that the CTCM and PCTCM models are not equivalent. Therefore, the CRS-A demonstrated discriminant trait validity; that is, correlations between any one function and items belonging to other functions were consistently low.

Method Effects. Method effect, or method bias, occurs when the instrument itself is influencing the assessment of traits (Byrne, 2013, p. 285). For example, method bias in the CRS-A would be present if Social, Directive, and Self were more highly correlated when measured with the CRS-A than when measured with the TALE. It is thought that method effects largely reflect respondents' desire to be consistent in self-reports (Bryant, 2000, p. 121). However, some self-report instruments can, based on wording, length, tone, and other factors, demonstrate more method bias than another self-report instrument measuring the same construct (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003, p. 882). Method effects are assessed by comparing CTCM and CTUM models. A significant discrepancy between the two models is evidence of method effects (Byrne, 2013, p. 300).

Results showed that the adjusted difference in fit between the CTCM (baseline) model and the CTUM model was also significant, $\overline{T}_d$ (36) = 279.27, $p < .001$. Per the Byrne (2013) MTMM protocol, a significant difference between the CTCM and CTUM models is indicative of discriminant validity in terms of methods. Table 21 lists the factor correlation between the Social, Directive, and Self functions and the CRS-A and TALE. The average correlation between the Social, Directive, and Self scales was .77 for the CRS-A compared to .74 for the TALE. Comparisons of the following indices were within tolerable levels ($\Delta < .01$): $\Delta RMSEA = .001$ and $\Delta NNFI = -.001$. However, as the *CFI* is the most appropriate fit index for MTMM comparison tests (Byrne, 2013, p. 301; Cheung & Rensvold, 2002), at $\Delta CFI = -.019$ was outside the .01 tolerance level (Hu & Bentler, 1999). Therefore, the CRS-A was found to exhibit method bias.

Hypothesis 3 Conclusion

Results of the MTMM CFA contrast tests indicated that the CRS-A, when configured in terms of the theoretical 3-function model empirically validated by the TALE (Bluck et al., 2005; Bluck & Alea, 2011), demonstrated convergent and discriminant validity. As such, evidence suggests that the CRS-A measures the theoretical constructs of Social, Directive, and Self AM functions. Further, the CRS-A was found to possess method bias. This topic is explored further in the Discussion section.

Hypothesis 4 Analyses

Hypothesis 4 concerned cross-cultural differences in AM function use. Given the sensitivity of the CRS-A to the cultural influences of joint reminiscing, data collected from the CRS-A was ideal for Hypothesis 4 investigations. However, as mentioned, the results of Hypothesis 4 tests carry two caveats. One, the testing of this hypothesis was strictly exploratory. Although much theory exists to justify the investigation, to date, no validated AM functions scale has been used to test cross-cultural differences in AM function frequency. Therefore, no specific predictions were made. Two, results yielded from this set of analyses are strictly provisional. Best research practices dictate that data used to validate a scale cannot be then used to measure the behaviors that the scale was designed to evaluate (Boslaugh, 2007). Therefore, Hypothesis 4 test results are to inform future research only.

The first part of Hypothesis 4 addressed differential use of AM functions across ethnic groups in terms of frequency. To test, scale scores were created for each of the six CRS-A functions (Conversation, Perspective-Taking, Relationship Maintenance, Behavioral Control/Teaching/Problem-Solving, Emotion Regulation, and Self) using SPSS 21 (IBM Corp., 2012). Table 22 summarizes the means and standard deviations of the CRS-A scale scores for the corresponding dataset. Given the provisional nature of the Hypothesis 4 analyses, and because the CRS-A was validated for use with the Caucasian and AAB groups only, all Hypothesis 4 analyses were run on the dataset used to validate the CRS-A for cross-cultural use, which included Caucasian (n = 451, randomly selected) and AAB (n = 451) respondents. Regression analysis was conducted to test whether ethnicity predicts the frequency with which each of the six AM functions are used. Significance level was set at $\alpha = .05$. The first set of analyses tested whether respondent ethnicity predicted respondent frequency of AM function use. Ethnicity categories were converted to dummy vectors prior to analysis using SPSS 21 (IBM Corp, 2012).

Results of regression analysis showed that ethnicity significantly predicted scores on the Conversation factor, $F(1, 900) = 11.34$, $p = .001$. Although the effect was small ($R^2 < 2\%$), results suggest that past-talk for the purpose of Conversation is engaged in with significantly greater frequency among Caucasians ($M = 4.97$, $SD = .94$) than among African-American/Blacks ($M = 4.74$, $SD = 1.08$), $b = -.11$, $t(901) = -3.37$, $p = .001$. This suggests that, per Kulkofsky and

Koh's definition of the Conversation function (2009, p. 460), that Caucasian group members are more likely to talk about the past as a means to promote conversation than are people in the AAB group.

Regression analysis also showed that ethnicity significantly predicted scores on the Behavioral Control/Teaching/Problem-Solving factor, $F(1, 900) = 14.16$, $p < .001$. Again, the effect was small ($R^2 < 2\%$), but results suggest that past-talk for the purpose of Behavioral Control/Teaching/Problem-Solving is engaged in with greater frequency amount African-American/Blacks ($M = 4.68$, $SD = 1.18$) than among Caucasians ($M = 4.40$, $SD = 1.02$), $b = .227$, $t(901) = 3.76$, $p < .001$. Per the Kulkofsky and Koh definition of the Behavioral Control and Teaching/Problem-Solving functions, members of the AAB group are more likely to talk about the past to teach lessons and/or solve everyday problems (2009, p. 460) than are members of the Caucasian ethnic group.

Ethnicity did not significantly predict Perspective-Taking ($b = -.07$, $t(901) = -.80$, $p = .427$), Relationship Maintenance ($b = .04$, $t(901) = .46$, $p = .645$), , Emotion Regulation ($b = .05$, $t(901) = .62$, $p = .534$), or Self. ($b = .05$, $t(901) = .54$, $p = .587$). The *n. s.* results suggest that these four functions are used with equivalent frequency regardless of ethnic affiliation.

The second part of Hypothesis 4 used data from the revised Multigroup Ethnic Identity Measure (MEIM-R) (Phinney & Ong, 2007) to predict past-talk behavior cross-culturally. Specifically, this investigation addressed whether father or mother ethnicity predicted respondent past-talk frequency in line with the differential effects found for the broader groups. Given the results of the first part of Hypothesis 4, of interest was whether respondents whose father or mother was identified as Caucasian would engage in Conversation past-talk with more frequency than respondents whose father or mother was identified as African-American/Black. Likewise, of interest was whether respondents whose father or mother was identified as African-American/Black would engage in Behavioral Control/Teaching/Problem-Solving past-talk with greater frequency than respondents whose father or mother was identified as Caucasian.

Although the sample used for Hypothesis 4 analyses was restricted to Caucasian and AAB respondents, no restrictions were placed as to which ethnic category[12] a respondent could assign his or her mother and father. Father and mother ethnic categories were dummy coded into vectors in SPSS 21 (IBM Corp., 2012) before evaluating via regression.

Regression analyses showed that father's ethnicity significantly predicted Conversation, $F(7, 894) = 2.13$, $p = .039$. Again, the effect was small ($R^2 = 1.60\%$), but results suggest that respondents engage in Conversation-related past-talk with greater frequency when the respondent's father is Caucasian, $b = .259$, $t(901) = 3.69$, $p < .001$. No other category of father's ethnicity significantly contributed to the effect. Father's ethnicity also significantly predicted the frequency with which respondents engage in Behavioral Control/Teaching/Problem-Solving past-talk, $F(7, 894) = 2.70$, $p = .009$, $R^2 = 2.1\%$. Results showed that respondents who indicated that their fathers were African-American/Black engaged in past-talk for reasons associated with the Behavioral Control/Teaching/Problem-Solving function with significantly less frequency than did respondents whose fathers were identified as belonging to one of the other ethnic groups, $b = -.29$, $t(901) = -3.62$, $p < .001$. Father's ethnicity did not significantly predict the frequency with which respondents engage in past-talk behaviors associated with the functions of Perspective-Taking, Relationship Maintenance, Emotion Regulation, or Self.

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[12] SONA ethnicity/race categories: Caucasian, African-American/Black, Arab, Asian, Hispanic, Multiracial, Native American, Hawaiian/Pacific Islander, Other. Respondents also had the option to Decline to Answer, but no data in the corresponding dataset were missing.

Respondents' mother's ethnicity was also used to predict the frequency with which Caucasian and AAB respondents engage in past-talk in a series of regression analyses. Results showed that mother's ethnicity significantly predicted respondent's Conversation past-talk frequency, $F(7, 894) = 2.72$, $p = .009$, with mother's ethnicity explaining 2.1% of the model variance. Results of the coefficient analyses indicated that respondents who categorized their mothers as AAB engaged in significantly less Conversation behaviors than did respondents who categorized their mothers as belonging to one of the other eight ethnic categories, $b = -.24$, $t(901) = -3.42$, $p = .001$. As was the case with respondents' fathers' ethnicity, respondents' mothers' ethnicity also predicted the frequency with which respondents' engaged in past-talk regarding Behavioral Control/Teaching/Problem-Solving, $F(7, 894) = 2.76$, $p = .008$, $R^2 = 2.1\%$. Per the coefficients analysis, respondents who categorized their mothers as AAB engaged in Behavioral Control/Teaching/Problem-Solving past-talk with greater frequency than did respondents who categorized their mothers as belonging to other ethnic groups, $b = .31$, $t(901) = 4.10$, $p < .001$. Mother's ethnicity did not significantly predict the frequency with which respondents engaged in past-talk associated with Perspective-Taking, Relationship Maintenance, Emotion Regulation, or Self functions. As such, parent ethnicity differentially predicted the frequency with which respondents engage in Conversation and Behavioral Control/Teaching/Problem-Solving AM function use. These findings are in alignment with the respondents' own use.

Hypothesis 4 Conclusion

Although provisional, results of Hypothesis 4 suggest the differential use of CRS-A AM functions across cultures. Findings suggest that ethnicity predicts the frequency with which AM functions are used. Results showed that Caucasian group members compared to AAB group members use Conversation past-talk with more frequency. Results also showed that AAB group members compared to Caucasian group members use Behavior Control/Teaching/Problem-Solving past-talk with more frequency. These patterns held when respondent father and mother ethnicity was used to predict respondent's frequency of past-talk use. Results showed that when respondents' father or mother is Caucasian, respondents engage in more Conversation past-talk than do respondents whose parents belong to other ethnicities. Results also showed that when respondents' father or mother is African-American/Black, respondents engage in more Behavior Control/Teaching/Problem-Solving past-talk than do respondents whose parents belong to other ethnicities.

CHAPTER 4 DISCUSSION

Confirmation of Previous Research

The current study investigated an expanded view of "everyday" autobiographical memory (AM) function. Previous research empirically validated the existence of a long-standing theoretical model comprised of the Social, Directive, and Self functions (Baddeley, 1987, Bluck, 2009; Bluck et al., 2005; Bluck & Alea, 2011; Neisser, 1978). Recently, Kulkofsky and Koh (2009) proposed the Child-Caregiver Reminiscence Scale (CRS), which featured seven AM functions. The CRS was originally designed for use by socio-developmental researchers interested in the early development and socialization of AM functions, particularly those that occur in "everyday" joint reminiscence contests (Kulkofsky & Koh, 2009). The Kulkofsky and Koh validation study proposed two scales: One that was validated for use in early socio-development research, and one that aligned with adult-like theoretical functions (Kulkofsky & Koh, 2009, p. 458), which was not validated. Albeit with modifications, evidence from the current study largely supported the theoretical model proposed by Kulkofsky and Koh.

Additionally, results of MTMM CFA analyses showed that the CRS-A mapped onto the TALE (Bluck & Alea, 2010), providing further support for the theoretical 3-function model of Social, Directive, and Self. Although the current study found evidence in support of a new adult AM function, Perspective-Taking, MTMM results suggest that this AM function appears to be a facet of the Social function. The current study also found evidence, albeit somewhat circumstantial, that Cognitive Skills is not a defining function of past-talk in college age adults. Kulkofsky and Koh (2009) had identified Cognitive Skills as existing separate from the Social, Directive, and Self functions in parent-child interactions. As such, the Social, Directive, Self model appears to be both empirically and theoretically comprehensive. However, to declare that the TALE Social, Directive, and Self functions are higher-order constructs to the six functions of the CRS-A would be premature. Regression analysis in the current study showed that each of the three TALE functions uniquely predicted theoretically their corresponding CRS-A functions more strongly than they predicted those CRS-A functions with which they are not theoretically linked. However, all three TALE functions and five of six CRS-A functions were significantly intercorrelated, suggesting perhaps that the two scales provide the basis for different perspectives on an overarching construct. For example, the theoretical literature suggests that AM auxiliary functions are the very "building blocks of social competence" (Pohl, Bender, & Lachman, 2006, p. 746). Thus AM functions must work synergistically to ensure successful social interactions.

Finally, the current study aimed to corroborate claims that AM functions serve both normative and causal purposes (Demick et al., 2000, p. 213). Normatively, AM functions were found to operate in everyday contexts. The incorporation of the joint reminiscence context ensured the elicitation of functions necessary to real-world events (Kulkofsky & Koh, 2009). For example, the theoretical scale from which the CRS-A was adapted was not restricted by theory, but guided by it. Thus the CRS-A was able to reveal everyday functions otherwise obscured by the theory-centric TALE (Bluck et al., 2005; Bluck & Alea, 2011). Causally, differences and similarities in AM functions were found as a function of culture. Differential use of the CRS-A Conversation and Behavior Control/Teaching/Problem-Solving functions was found between Caucasians and African-American/Blacks. This, too, was demonstrated as a result of the joint reminiscence context, which activates social and cultural influences on past-talk content and use (Kulkofsky & Koh, 2009).

Study Strengths and Novel Contributions

The current study was unique among AM function studies in several ways. On the macro level, it adapted the theoretical but unvalidated CRS, which proposed an expanded set of adult-like AM functions beyond the long-held theoretical Social, Directive, and Self functions recently validated by the TALE (Bluck et al., 2005; Bluck & Alea, 2011).

The current study was designed to ground AM functions in ecological theory, and the CRS provides an ideal springboard. The CRS instantiated AM functions within context of joint reminiscing. Joint reminiscing was of particular interest to the current study for two reasons. The first is its lifelong influence on the nature of everyday AM functions, and thus its continuing role in the socialization of AM functions. The second reason to develop an understanding of joint reminiscence is that such an understanding forms the basis for models of the relation between the functions of AM, and the mechanics and development of AM. The current study's CRS-A yielded evidence for a novel set of everyday AM functions that expand and empirically explicate the long-held theoretical model without contradicting or negating it.

On the micro level, the CRS-A was derived through statistical methods and software unavailable at the time to developers of the CRS. The use of R-Factor (Basto & Periera, 2012) allowed for the construction and analysis of a factor analysis model underlain by naturally ordinal, nonnormally distributed data. R-Factor also provided diagnostics and results appropriate for such data, improving the accuracy of conclusions and interpretation.

The current study also conducted rigorous psychometric tests beyond that previously reported in the AM functions literature. A structural equation modeling approach using estimation (robust unweighted least squares) and fit indices (Satorra-Bentler chi-square) appropriate to ordinal-level nonnormal data, was used to validate the CRS-A. The current study also conducted the following novel analyses for the AM function literature. First, a series of MGCFAs were conducted to test the reliability and invariance of the CRS-A over time, gender, and ethnicity/race, supporting the view that the CRS-A operated equivalently for all tested groups. Next, a series of MTMM analyses were run in conjunction with the TALE to test construct validity (convergent and discriminant) and method effects. Results indicated that the CRS-A demonstrated convergent and discriminant validity. The use of MTMM in the current study is particularly novel, as previous AM function scale validation studies have relied solely on correlation and regression analysis. It is also the first study in which method bias was reported, although the discovery of method bias has some strengths. For one, awareness of method bias in this domain alerts administrators of not only the CRS-A, but also the CRS and TALE of the need to investigate any self-report measure in the domain of AM function that potential issues of accuracy ought to be taken into account. Validation of self-report measures against observational measures is an obvious need in this domain.

The current study supported the majority of the theoretical CRS model, even if it had not been validated with their sample data (Kulkofsky & Koh, 2009, p. 461). The most substantial change was the elimination of the Cognitive Skills function from the adult model, which is not entirely surprising on the basis of both empirical findings and statistical methods employed. One, correlation analyses conducted by Kulkofksy and Koh showed that, as children aged, caregivers engaged in Cognitive Skills joint reminiscing with significantly less frequency (2009, p., 465). Granted, the child age range in the Kulkofksy and Koh study was only 2–6 years, but AM research suggests that autobiographical memory development, at least in terms of ability, is achieved by adolescence (Fivush, 2011, p. 559) or perhaps even earlier (Bauer, 2012). Therefore, it is reasonable to expect that Cognitive Skills past-talk—"talking about the past to teach a child how to remember" (2009, p. 460)—is no longer an essential function by early adulthood. Two, the statistical method used by Kulkofsky and Koh to derive the CRS model is notorious for overextracting; i.e., yielding a model with more factors than is statistically viable (Basto & Pereira, 2012, p. 5). Specifically, the principal factor analysis (PAF) that Kulkofsky and Koh conducted used the Kaiser method of extraction (2009, p. 463; Basto & Pereira, 2012, p. 5). Although they report that the inclusion of Cognitive Skills items in the model accounts for additional explained variance, such is a well-known consequence of increasing number of items in factor analysis regardless of items' actual meaningfulness to the model (Nathans et al., 2012, p. 8). Cognitive Skills could have simply been an artifact of the PAF technique used by Kulkofsky & Koh (2009, p. 463). Three, the results of the CFA run on 7-model CRS-A also indicated that too many variables were being used to explain the construct (Raykov & Marcoulides, 2006, p. 49). However, once cognitive skills was removed, model fit improved, residual error decreased, and the convergence problems that had plagued attempts to run MGCFAs on the 7-function CRS-A model ceased. Evidence suggests that the 6-function CRS-A, at least for adult samples, is both statistically and theoretically valid. Note that this does not imply that the maintenance or development of cognitive skills are not a valid function for all adults given that the current study's sample was restricted to college students. For example, a CRS-A with an appropriate set of items developed for slightly older adults might find that cognitive skills is a necessary domain for that age range.

Another change involved the CRS functions of Behavior Control and Teaching/Problem-Solving, which united in the EPAF of the current study. It is difficult to determine if behavioral control items were perceived as problem-solving items or vice versa. Items from both functions loaded positively on the single factor. This implies that people engage in the associated joint reminiscence behaviors more frequently when opportunities to problem solve exist, or when feeling confident enough in one's wisdom and integrity to share those seeking guidance. In either case, the skills needed to exert behavioral control and/or to successfully teach or solve problems have likely, by adulthood, been assimilated. As such, there may be a greater need in adulthood to *apply* such skills. If, for example, a lack such skills were seen by one's social system as unacceptable, then modifying one's behavior accordingly by recalling and past-talking about more appropriate reference behaviors—hence "problem-solving"—may be a more tenable explanation for adults. Nor may adults distinguish the use of past-talk to "emphasize consequences of negative behavior," or to "clarify moral lessons" (both from the CRS Behavioral Control function), as operationally different from using past-talk to "help myself and others problem-solve," or "see how my or another's strengths can help solve a present problem" (both from the CRS Teaching/Problem-Solving function). In any case, the combined items were verified to be a single function in the CFA.

The final change to the CRS model involved two items from the CRS function of Relationship Maintenance, which loaded on their own factor. Semantically, the two items, "I use past-talk in order to help me understand others" and "I use past-talk to understand how others feel about an event" were the only two Relationship Maintenance items that used the word "others" rather than "another," "family members," or "friends." It may be that the specificity of "friends" and "family" conjured contexts of greater intimacy for respondents than did the use of generic "other." As the items are clearly getting at using joint reminiscing to "know" another, this factor appears to be getting at perspective taking. Like the remaining Relationship Maintenance items, these items loaded negatively on the perspective-taking (PT) factor. This implies that respondents engage in these joint reminiscence behaviors more frequently when their understanding the other is low. This is also plausible given the adult sample, as there may be little need for a caregiver and child to perspective-take, largely because a child has not yet developed the sophisticated sense of others' minds essential to perspective-taking (Goldman, 2006, p. 83). in the child-caregiver. For example, theory of mind does not begin to emerge until the ages of 3–4 (Bower, 1993), which is the target age range of the CRS. Although these two items will be tested with the CFA as belonging to a new factor, caution will be exercised given earlier indications that the model was overexplaining the construct. As such, it may have been interpreted by adult respondents as lacking a degree of intimacy necessary for inclusion with "relationship" specific items. This is plausible given that adult relationships span myriad degrees of intimacy, whereas the child-caregiver relationship is unlikely to be perceived as casual.

The current study also found evidence for the use of past-talk to be used as a resource used to fill a psychosocial need. Although the CRS-A Conversation and Behavioral Control/Teaching/Problem-Solving items loaded positively onto their factors, items for the CRS-A Relationship Maintenance, Perspective-Taking, Emotion Regulation, and Self loaded negatively. Table 10 lists the factor loadings per item and Table 11 lists the factor correlations per function. This is in contrast to results of the validated CRS, of which all factors are presumably positive (Kulkofsky & Koh, 2009). Typically, loading direction is interpreted such that the sign indicates the relation between item and factor (Bryant & Yarnold, 1995). That is, positive loadings indicate that people who score highly on the item score highly on the factor[13]. Negative loadings indicate that people who score highly on the item score low on the factor. This implies that the CRS-A may have tapped into the trait-like properties of the AM functions, whereby people use past-talk to promote, improve, or sustain mental states, social dynamics, or self-continuity. For example, items loaded negatively onto the CRS-A Self function, implying that people talk about past with respect to self when the need to feel good about oneself (CRS-A item 32), or the need build a unique identity (CRS-A item 34) is high, but engage in these past-talk behaviors with less frequency when those needs are low.

The factor correlations of the EPAF (Table 11) showed similar patterns. For example, individuals who tend to report relatively frequent use of Conversation are also high on the functions of Perspective-Taking. However, individuals who report relatively nonfrequent use of Conversation report relatively frequent use of Relationship Maintenance, Behavioral Control/Teaching/Problem-Solving, Emotion Regulation, and Self functions. This suggests that, people who are already knowledgeable about others (as would be likely with friends or family), or who are either skilled or naturally astute perspective-takers, past-talk to aid the inferencing of another’s thoughts or feelings is unnecessary. In such cases, informal, or conversational, past-talk prevails, especially when interacting with acquaintances rather than friends or family. However, individuals who use past talk frequently to maintain social ties (Relationship Maintenance), solve problems (Behavioral Control/Teaching/Problem-Solving), gain emotional

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[13] The designation of a positive or negative pole for an individual factor is done in the context of the other factors. Although the model reflects a six-dimensional space, only two dimensions can be considered at a time. Therefore, negative loadings of a particular factor in the EPA that become positive in the CFA by changing the correlations of that factor.

footing (Emotion Regulation), or maintain self-continuity (Self), have perhaps more pressing needs to employ past-talk for purposes other than chitchat. As the items that loaded onto the Perspective-Taking function reflect past-talk for the purpose of understanding "others" versus "friends" or "family," it may be that people who use perspective-taking past-talk relatively frequently do so only with strangers or less familiar acquaintances, with whom heavier past-talk topics would be inappropriate.

Likewise for the CRS-A Directive function of Emotion Regulation, the items of which also loaded negatively. This suggests that people in need of emotion regulation use corresponding past-talk to facilitate coping with stressful or upsetting information (CRS-A item 28), but use such past-talk with less frequency when already proficient in executing an appropriate emotional response (CRS-A item 26). Contrarily, the CRS-A items associated with the Directive function of Behavioral Control/Teaching/Problem solving loaded positively. This implies that people use affiliated past-talk with greater frequency when the need to do so is high. For example, one need not engage in past-talk that facilitates the solving of problems (CRS-A item 22), or to ensure that a past mistake is repeated (CRS-A item 23), unless a hardship or threat to one's ability to handle a particular situation exists[14].

Positive items also occurred on the CRS-A Social function of Conversation. This may suggest that conversation is frequent when social opportunities to engage in past-talk are plentiful. For example, people who engage in past talk to share personal experiences with another (CRS-A item 4) will likely do so only when such conversation is appropriate; i. e., that there exists either trust, closeness, or other factors that contribute to self disclosure (Greene, Derlega, & Mathews, 2006, pp. 412–413). Contrast this with the fact that factor loadings for the

[14] Note: If the items on one of these factors were *reflected* (i.e., 7 becomes 1, etc.), the direction of the correlation between the factors would change.

Social auxiliary function of Relationship Maintenance were negative. This implies that, when social relationships are strong, Conversational past-talk is prevalent, but Relationship Maintenance past-talk is less warranted. For example, people who feel cared for are less likely to engage in past-talk to remind themselves of such (CRS-A item 9). Likewise, the loadings for the remaining Social function, Perspective-Taking, were negative. This suggests that perspective-taking past-talk is used more frequently when information about the other's thoughts and feelings are unknown or noninferable. For example, people who use past talk to understand how others feel about an event (CRS-A item 8) would do so with less frequency than when one has prior knowledge or good insights into others' internal states. Thus the direction of Social loadings together reveal the synergy of the Social subfunctions: When relationships are information or intimacy poor, joint reminiscing for the purpose of relationship maintenance and perspective-taking is used, whereas, when relationships are stable, people turn to Conversational past-talk.

The discovery of the CRS-A function of Perspective-Taking also lends novelty to the current study, as no previous AM scale validation study reported evidence of its existence. That it was not detected in the validation study of the CRS is unsurprising. The development of perspective-taking capacities does not occur until around the age of four (Nelson, 1993), and the Kulkofsky and Koh child sample was between two and six (2009, p. 461). However, for adults, the theoretical literature states that perspective-taking is an important function served by AM (Alea & Bluck, 2003; "Autobiographical Memory," n. d., p. 17). The application of one's own experiences to the predicting of another's behavior is a vital social skill that facilitates social interaction and fosters closeness (Pohl, Bender, & Lachman, 2005, p. 746) Yet, perspective-taking as a function of AM has gone largely unexamined empirically. The current study therefore provided evidence that narrowed that gap.

In addition to the current study finding evidence of a new auxiliary AM function, Perspective-Taking, it also found evidence against CRS function Cognitive Skills (Kulkofsky & Koh, 2009). Results of numerous fit indices and statistical assessments rendered the Cognitive Skills function unviable for adults. This finding is plausible from a theoretical perspective. Kulkofsky and Koh's characterized the CRS Cognitive Skills function as specifically serving developmental and socialization goals, possibly even more so than the other functions (2009, p. 460). Their own evidence that the frequency with which caregivers use Cognitive Skills past-talk with their children as the child ages suggests that the need to develop such skills unlikely prevails beyond childhood. That, however, does not imply memory-skill building is irrelevant to adults. Rather, the CRS may have tapped into the *acquisition* of skills necessary to remembering, which in adulthood is peripheral to the *application* of memory skills. In that light, using past-talk to see how far back one can remember (CRS-A item 37), or to improve one's ability to convey past experiences and memories to others (CRS-A item 41), seems unlikely. Ultimately, neither statistical evidence nor theoretical argument justified an adult Cognitive Skills AM function, but as noted above, this may be a function of the limited age range of the participants.

Finally, the current study found provisional empirical evidence for the differential use of AM functions across ethnic groups. Although results of the current study addressing this line of inquiry are provisional only—their purpose was to inform future hypotheses—they are nonetheless important. Related research has found substantial evidence for cultural influences on the content of memories (Conway, Wang, Hanyu, Haque, 2005, p. 739). Results of the current study suggest that why we engage in past-talk is likewise culturally sensitive.

Results showed that the Caucasian group engaged in Conversation past-talk with significantly greater frequency than did the African-American/Black group. Given that items loaded positively on the Conversation function during PAF, this loading pattern suggests that people engage in Conversation past-talk more frequently when high on the “trait” level of Conversation. Although the AM functions are not “traits” in the typical sense, they underlie the behaviors that indicate the functions. For example, people may engage in Conversation-related past-talk more frequently when current social relationships facilitate conversational, rather than or instead of, other purposes for past-talk. Contrarily, people low in conversational opportunities may be less likely to initiate conversation with past-talk and turn instead to “small talk” (Goldsmith & Baxter, 1996). Research shows that, overall, people rate “small-talk” reminiscing as informal and positive, at least initially (Goldsmith & Baxter, 1996, p. 101). That members of the Caucasian group engage more frequently in Conversation past-talk than do members of the African-American/Black group may be due to a wider acceptance in Caucasian cultures to use small-talk for the fulfillment of relationship goals, whereas other groups may regard such as manipulative (Goldsmith & Baxter, 1996, p. 89).

Contingently, the idea of using past-talk for goal fulfillment could pertain to the use of past-talk to facilitate decision-making, instruction, and the sharing of advice (Goldsmith & Baxter, 2006, p. 102). As the CRS-A Behavior Control/Teaching/Problem-Solving function was positively correlated with its items, past talk involving instruction, decision-making, and the offering of advice likely occurs with more frequency when people have, or perceive themselves to have, circumstances necessitating resolution or repair. In the current study, African-American/Blacks engage in Behavioral Control/Teaching/Problem-Solving past-talk with significantly greater frequency than do Caucasians. This finding could reflect recent evidence that life narratives of African-Americans reflect more chronic negativity and the challenges that come with the associated problems (oppression, loss of control, discrimination, poverty, low socioeconomic status) than do the life narratives of people of Caucasian ethnicities (Coleman, 2012, p. 39). Thus the urgency of solving these problems may be given priority over reflection and chatting about the past. Therefore, as an adaptive measure, negative life consequences are often attributed to externals like poverty to avoid blaming oneself for perhaps insurmountable, interminable predicaments (Coleman, 2012, p. 41). Tables 10 and 11 list factor loadings and unattenuated factor correlations for the 6-function derived through principal factor analysis using R-Factor. Tables 12 and 13 list the factor loadings and unattenuated factor correlations from CFA using a structural equation modeling approach.

Study Limitations, Issues, and Nonsignificant Findings

Although findings from the current study add to the empirical and theoretical AM functions literature, a number of limitations warrant discussion. The CRS-A was adapted from a theoretical scale that was assumed by its developers to reflect “adult-like” AM functions, but which had not been statistically validated as such. As such, CRS-A adapted items may not reflect a truly representative set of past-talk behaviors more relevant to adult AM. Although factor analysis, confirmatory factor analysis, MGCFAs and MTMM analyses of the adapted scale revealed the theoretically structure proposed by Kulkofsky and Koh (2009) to be viable, both the emergence of the Perspective-Taking function and the rejection of the Cognitive Skills function (to permit multigroup structural equation modeling invariance testing) invite confirmation through replication with fresh data and wider sampling of the adult age range and educational levels.

Another possible limitation of the utility of the CRS-A is the discovery of method bias. As method effect tests were not performed on the CRS (Kulkofsky & Koh, 2009) or the TALE (Bluck & Alea, 2011), the detection of CRS-A method bias in the current study may implicate its presence in similar AM function scales. The most obvious suspect of CRS-A method bias is joint reminiscence, the context elicited for CRS-A items but not for items of the TALE. Because the current study administered its scales through the online SONA prescreen, there was a limit to the number of items allowed. Future studies should include a third AM functions scale as an additional MTMM method in order to triangulate the source of the method effect. For example, had the current study included the Reminiscence Functions Scale (Webster, 1997), which, like the TALE, is not designed to elicit the context of joint reminiscence, perhaps pairwise comparisons across methods would have teased out (or eliminated for consideration) joint reminiscence method effects. As for other sources of method effect, that the CRS-A is a self-report scale may have contributed to this, as rater's responses often reflect more than estimations of the frequency of certain behavior (Podsakoff et al., 2003, p. 881). For example, items that implied a need to cope (CRS-A item 28), be accountable for negative behavior (CRS-A item 17), or feel loved (CRS-A item 9), may have compelled respondents who perceive their own such behaviors as negative to respond in more socially desirable ways (Podsakoff et al., 2003, p. 882). From a statistical standpoint, resultant correlations based on such responses reflect some degree of true behavioral information, but also artifacts of ideal or preferred behavior (Podsakoff et al., 2003, p. 881). Thus results of the current study should be interpreted with this in mind.

Although the current study found evidence for the trait-like nature of AM functions by way of positive and negative factor loadings, supporting data with which to verify these results were not available. Ideally, correlation and regression analyses of CRS-A factor scale scores and personality measures would have been greatly informative. For example, if high scores on neuroticism predicted high scores in the CRS-A Emotion Regulation function, such would have supported the current study's contention that people engage in Emotion Regulation past-talk with more frequency when emotion regulation is low. Likewise, if people high in extraversion scored high in Conversation, such would have supported the current study's contention that people engage in Conversation past-talk with less frequency when opportunities to do so are scarce. However, this effect may be a function of extraversion, whereby people high in extraversion may be more apt to have constructed a personal social milieu conducive to Conversation past-talk. Although the current study arranged to incorporate personality data for the purpose of illuminating such findings, inconsistencies in subject identifiers in collection of this data for the current study required that this particular program of planned analyses be abandoned. In addition to individual differences in personality, future studies should examine differences related to current and former family dynamics, as such may impact the type of past-talk that an individual finds sufficiently valuable to use frequently.

Another limitation to the current study was that, despite inclusion on the SONA prescreen, it failed to acquire ethnic group samples large enough for MGCFA. Exacerbated by CRS-A model complexity, even the inclusion of groups of $n > 200$ resulted in nonconvergence when the number of groups exceeded two. As such, only the Caucasian and African-American/Black groups could be compared. Given that the literature reports much related research on Asian (Fivush, 2011; Kulkofsky et al., 2008; Markus & Kitayama, 1991; Miller, Wiley, Fung, & Liang, 1997; Wang, 2001, 2004; Wang & Fivush, 2005) and Arab (Nefs-Zehngut, 2011) groups, the current study was unable to produce supporting empirical evidence.

The current study had also planned to incorporate information from the MEIM-R. The MEIM-R allows respondents to identify the ethnic group or groups with which they feel most affiliated (Phinney & Ong, 2007). Such is important in light of research indicating that the ethnicity/race categories typically provided in demographic questionnaires are far too limiting (Phinney & Ong, 2007); respondents are forced to choose superficial classification that may reflect an incomplete picture of one's ethnic affiliation. As an objective of the current study was to investigate cross-cultural differential use of AM functions, such data seemed more informative to this purpose than conventional demographic data. However, the current study underestimated the enthusiasm with which respondents would supply ethnic information. Of 1841 cases, 27 were not unique; i.e., few respondents chose simply "Caucasian," or "African-American/Black." Instead, most respondents provided multiple and nonredundant ethnic affiliations (e.g., "Scottish/Norwegian"; "Indian, Russian, White"). Thus, the level of noise in this data precluded its use in the current study.

Implications and Future Directions

The validation of the CRS-A for adult samples is an important contribution to the AM literature in particular and social-cognitive literature in general, particularly with respect to the empirical validation and expansion of long-held theory. Both the CRS (joint reminiscence in child-caregiver context) and TALE (empirical validation of the theoretical 3-function model) have been validated as useful for the purposes they set out to do. But the CRS-A offers extended utility, in that it is useful across time, gender, and ethnicity. It also refines the TALE model to include aspects of the three that may be of more use to some domains of research, allowing AM researchers to explore a greater repertoire of research questions, expand existing theory, and develop new empirical investigations. For example, the contextual and dynamic nature of joint reminiscing makes it fitting for research on the ecological, situated nature of AM.

The CRS-A and findings yielded from its use is of value to both AM researchers and researchers in related domains concerned with social, cognitive, and developmental factors that may drive behaviors of interest. That the CRS-A was found to have configural utility across gender and ethnic groups supports the treatment of each function and its items as its own subscale. As such would lend greater utility to the CRS-A within more contexts and across more domains, future research should investigate the reliability of using subscales as stand-alone instruments.

More empirical work is also needed on Perspective-Taking as an AM function. That the current study found evidence of this function with only two items suggests that, although compelling, is not being broadly captured. Future studies should consider what perspective-taking past-talk is absent from the current model, and generate additional items. Also, because no additional measures were available in the current study with which to further support the Perspective-Taking function, future studies should incorporate subscales like the IRI Perspective-Taking subscale (Davis, 1983), and other empathy subscales to better align empirical results to theory.

Finally, future studies should consider the existence of another AM function related to perspective taking: mental time travel (MTT). MTT is the prospection of past events via which future events are imagined or predicted (Shanton & Goldman, 2010, p. 32). Necessary to MTT is the ability to “recombine” one’s past experiences into an unforeseen but prophesied future (Shanton & Goldman, 2010, p. 32). Whereas perspective-taking requires one to detach oneself from an inner mental state in order to imagine that state being experienced by another (Shanton

& Goldman, 2010, p. 32). MTT requires the detachment of oneself from one's present state to image that state being experienced in the future (Shanton & Goldman, 2010, p. 32). As research suggests that most people engage in MTT (Shanton & Goldman, 2010), there may be an AM function specific to its achievement. Although two CRS-A items imply using past-talk to promote successful future outcomes (Item 21, "I use past-talk to prepare myself for an upcoming event," and Item 23, "I use past-talk so that I or another avoids repeating a past mistake at some later date"), no item in the CRS-A specifically address past-talk for MTT (an example item being, "I use past-talk to help me imagine what might happen to me in a future situation"), future studies should consider generating and testing such items.

CHAPTER 5 HUMAN SUBJECTS

The primary component of the current study was a 77-item online questionnaire included in the prescreen of the conducting university's experiment management system (SONA). Participation was worth 0.50 credit hours for approximately 15 minutes of time to complete the current study's portion of the questionnaire. Credit was automatically posted to each participant's individual SONA account no later than 24 hours following prescreen completion.

The primary component of the proposed questionnaire was the 41-item CRS-A (plus two general questions); the 15-item TALE (plus two general questions); and the 6-item MEIM-R (plus 4 general questions). Participants who wish to enroll in any SONA-managed psychology study must first qualify for that study through the completion of the online prescreen questionnaire. The prescreen is preceded by an informed consent form (Appendix A) and set of instructions specific to each included instrument. Participants were not asked to provide their age, but were required to verify (Yes/No) that he or she was 18-years-of-age or over. Participants were instructed that by participating in the prescreen, he or she understands and agrees to the terms of the informed consent. Participants had the option to discontinue the prescreen at any time. However, outside of the Principal Investigator's control, SONA does not issue any portion of the 0.50 credit hours to any participant who does not complete the prescreen. Participants were recruited through the SONA system exclusively. Eligibility to participate in SONA studies is dependent on the participant's enrollment in a SONA-participating psychology course. SONA tallies and reports each participating student's completed credit hours, but course instructors have the discretion to offer or not offer extra credit based on SONA participation. Participants were assumed to be primarily of traditional college age. SONA participants younger than 18 are waived from obtaining parental permission to participate in the prescreen per the conducting University's waiver of parental permission.

Data collection and tracking was managed by the SONA system, which ensured the privacy of individuals and confidentiality of data. Although the current study's hypotheses were not revealed to participants, no deception was deemed necessary and was therefore not employed. Nor was the general student pool from which current study participants were recruited considered high-risk. Therefore, the current study posed no physical or psychological risk to participants.

Benefits of participation in the current study included the fulfillment of psychology course research participation credits and/or extra credit. Findings from the current study are expected to further the field of social cognition generally, and will add to the autobiographical memory and reminiscence literatures specifically.

APPENDIX A

Informed Consent

Behavioral Research Information Sheet
Title of Study: ***Everyday Memory***
Principal Investigator (PI): Jana Ranson
Psychology Department
(313) 577-2811

Purpose
You are being asked to be in a research study on the various ways that people use everyday memory because you are enrolled in a psychology class and have expressed an interest in participating in research. This study is being conducted at Wayne State University. The estimated number of study participants to be enrolled in the study at Wayne State University is about 1500. Please read this form before agreeing to be in the study.

Study Procedures
If you agree to take part in this research study, you will be asked to answer several questions about yourself and about your everyday memory. You will answer these questions directly on the SONA system. This study involves only one session and its total duration is expected to be approximately 15 minutes.

All of your completed testing materials will be kept on a secure server and on the PI's computer in a locked research laboratory. Information on the PI's computer will not be connected to your name in any way. All responses will be kept strictly confidential. Your data will not be individually identified in any publications or presentations that may stem from this research; only aggregated data will be presented.

Benefits
The possible benefits to you for taking part in this research study are that you will be contributing to scientific knowledge in the areas of memory, social-cognitive psychology, and personality psychology. Gaining knowledge in these areas is important because it helps us to understand how memory is developed and used. In addition to increasing knowledge, this study will also expose you to the methods utilized by psychology researchers. Furthermore, responding to these types of questions allows for you to reflect on your personal views and experiences as you think about your responses to the items.

Risks
There are no known risks for participating in this study.

Compensation
Compensation for participation in the prescreening is twofold. First, you will receive ½ credit of research participation for participating in the prescreen. If you choose to stop your participation in the prescreen, or if you choose not to answer specific questions, then you will still receive this credit. Second, participation in the prescreen measures allows you access to other studies for which you can earn more research credits.

Confidentiality
All information collected about you during the course of this study will be kept confidential to the extent permitted by law. You will be identified in the research records by a code name or number. Information that identifies you personally will not be released without your written permission. However, the study sponsor, the Human Investigation Committee (HIC) at Wayne State University, or federal agencies with appropriate regulatory oversight [e.g., Food and Drug Administration (FDA), Office for Human Research Protections (OHRP), Office of Civil Rights (OCR), etc.] may review your records.

When the results of this research are published or discussed in conferences, no information will be included that would reveal your identity.

Voluntary Participation/Withdrawal
Taking part in this study is voluntary. If you decide to participate, you may withdraw from the study at any time without penalty and without loss of benefits to which you are otherwise entitled. If you withdraw from the study before data collection is completed your data will be returned to you or destroyed. You have the right to omit any question(s)/procedure(s) you choose. Your decisions will not change any present or future relationship with Wayne State University or its affiliates, or other services you are entitled to receive.

The PI may stop your participation in this study without your consent. The PI will make the decision and let you know if it is not possible for you to continue. The decision that is made is to protect your health and safety, or because you did not follow the instructions to take part in the study

Questions
If you have any questions about this study now or in the future, you may contact Carissa Broadbridge, M.A. at the following phone number 313-577-2811. If you have questions or concerns about your rights as a research participant, the Chair of the Human Investigation Committee can be contacted at (313) 577-1628. If you are unable to contact the research staff, or if you want to talk to someone other than the research staff, you may also call (313) 577-1628 to ask questions or voice concerns or complaints.

APPENDIX B

Online Prescreen Instruction Page

This study is an online survey administered by the system. Participants are only identified to researchers with a unique numeric ID code.

Listed below are questions for this section of the survey. Please provide a response for every question. If you are given the option to decline to answer a question, then declining to answer is considered a response.

This study consists of an online survey, which you may now participate in. You will receive credit immediately upon completion of the survey. The survey consists of a number of multiple-choice and/or free-answer questions, and may be divided into a number of sections. You must complete all sections in one sitting, as you are not allowed to resume at another time from where you left off. While you are participating, your responses will be stored in a temporary holding area as you move through the sections, but they will not be permanently saved until you complete all sections and you are given a chance to review your responses.

Appendix C

Issues in the Assessment of Model Fit

The following describes methods and procedures used for the analyses detailed in the Results section.

Assessment of Model Fit

The following sections detail the criteria used in the current study to evaluate results.

Feasibility of iterative parameter estimates. The following criteria had to be met for a model in the current study to be considered reasonable. Models that did not converge were considered misspecified, and were either re-configured or excluded from further consideration. Before disregarding, aspects known to underlie nonconvergence were examined. Specifically, negative variances (Byrne, 1989, p. 54; Raykov & Marcoulides, 2006, p.32) and out-of-range factor loadings (Byrne, 1989, p. 54) can singularly or together cause nonconvergence. Therefore, all variance estimates were checked for violations. Likewise, results were examined for factor loadings falling outside the appropriate 0–1 range (Byrne, 1989, p. 54). However, regarding the latter, when factors are allowed to correlate (i.e., factors are *oblique* rather than *orthogonal*), loadings can exceed the correlational upper limit of 1.0 (Jöreskog, 1999, p. 1). Such loadings are not correlations, but are *regression coefficients*, and can, without harm to the model, be larger than 1.0 (Jöreskog, 1999, p. 1). Consistent with the procedures of Kulkofsky and Koh (2009), the factors in the current study were allowed to correlate; as such regression coefficients > 1.0 were not, in and of themselves, cause for concern. However, factor loadings > 1.0 did on occasion undermine models in other ways. For example, factor loadings > 1.0 may have inflated condition numbers, which reflect degree of multicollinearity (Kootstra, 2004, p. 11). Also, factor loadings > 1.0 were the likely cause of warnings that measurement error (theta-delta and theta-epsilon) matrices were not positive definite. Both condition numbers and error matrices were monitored for these issues, remedied if necessary and appropriate, and considered when interpreting results. Regarding the few models in the current study whose theta-delta matrices were not positive definite: Consensus in the literature is that, if the model converges and otherwise demonstrates good fit, any resultant "not positive definite" error messages can be ignored (Wothke, 1993, p. 266). Unless such occurrences were of issue in the model, that information is not discussed in the corresponding Results subsections.

Adequacy of measurement model. Squared multiple correlations (R^2) for all items were evaluated to ensure they were positive and within the acceptable range of 0–1.0. R^2 in the SEM context reflects how reliably the item is measuring its factor (Byrne, 1989, p. 54). Therefore, the closer the current study's R^2 values were to 1.0, the more reliable the items were interpreted to be. Likewise, the more reliable items there were in a model, the better the model was interpreted to be.

Goodness-of-fit of the overall model. Overall model fitness was assessed via the model chi-square (χ^2), degrees of freedom (*df*), *and p*-value. Two chi-squares reported in LISREL 9.1 (Scientific Software International, 2012) were used in the current study. Initial analyses (see Appendix D for details) used the *C2* chi-square as a way to remain aligned with Kulkofsky and Koh procedures. However, the *C2* chi-square also assumes MV normality, so is biased when data are neither continuous nor normal (Jöreskog, 2004, p. 1). Because the current dataset was MV nonnormal, the *C3* Satorra-Bentler chi-square was used in later CFA analyses, as it corrects for multivariate nonnormality (Jöreskog, 2004, p. 2). Although the *C4* also corrects for multivariate nonnormality, its use of WLS estimation has been found to return inconsistent when the model features > 20 variables, regardless if samples are large, so is not widely recommended (Lei & Wu, 2012, pp. 173–174), and was not used in the current study.

Subjective goodness-of-fit indices for overall model. Given that all model chi-square types are sensitive to sample size, overall model fit is not typically determined by the chi-square test statistic alone (Byrne, 1989, p. 54). Therefore, a variety of other fit indices were used in the current study, each derived on various parameters and model aspects, and each reflecting somewhat different psychometric properties of the model. Those fit indices included the chi-square to degrees of freedom ratio, root mean square error of approximation (*RMSEA*), nonnormed fit index (*NNFI*), comparative fit index (*CFI*), and the standardized root mean residual (SRMR). Each fit index is detailed, with its formula, below. Because LISREL is not consistent in which model chi-square it uses to compute the *RMSEA*, *NNFI*, and *CFI*, these three values for all models were calculated by hand. All fit index formulas used in the current study are provided below. Unless otherwise noted in the Results subsections of each analysis, all fit indices based on the model chi-square were calculated using the Satorra-Bentler (*C3*).

Chi-square to degrees of freedom ratio. This ratio is meant as a fit guideline for models with large samples, as a substantial *N* can drive significance regardless of how good the model (Römhild, 2008, p. 35). The formula is as follows:

$$\chi^2 \text{Ratio} = \frac{\chi^2_{SB}}{df_{SB}}$$

The ratio is often not reported, as there is currently no widespread agreement regarding cutoff (Kenny, 2013). However, per consensus in the literature, the current study considered model ratios < 5.0 as adequate (Bollen, 1989), with the best-fitting models falling below 2.0 (Byrne, 1989, p. 55). Additionally, ratios over 10.0 were thought to reflect inadequate models, whereas models with ratios less than 1.0 indicated that the model was too well fitting to be replicable (Schmitt, 1978, p. 162).

Root mean square error of approximation (RMSEA). The *RMSEA* reflects the degree of error between the observed and hypothesized (expected) models. The formula is as follows:

$$\mathrm{RMSEA} = \sqrt{\frac{\left(\frac{\chi^2_{SB} - df}{N-1}\right)}{df}}$$

The *RMSEA* formula adjusts for both sample size (*N*) and model complexity (df) out, so is not sample dependent. (Raykov & Marcoulides, 2006, p. 46). For the current study, the *RMSEA* was computed using the corrected Satorra-Bentler (*C3*) chi-square. Although values < .05 indicate a well fitting model, values < .08 reflect adequately fitting models (Hooper et al., 2008, p. 54). Note that the use of the *C4* (nonnormality corrected) chi-square in the current study would have yielded lower *RMSEA*s than those computed using the *C3* chi-square, but were reported because of the controversy over the *C4*'s accuracy and thus the accuracy of fit indices derived from its value (Lei & Wu, 2012, pp. 174‒175), it was considered untenable for the current study.

Nonnormed fit index (NNFI). Like the *RMSEA*, the *NNFI* accounts for model complexity by adjusting out the degrees of freedom:

$$\mathrm{NNFI} = \frac{\left(\frac{\chi^2_i}{df_i}\right) - \left(\frac{\chi^2_{SB}}{df_{SB}}\right)}{\left[\left(\frac{\chi^2_i}{df_i}\right) - 1\right]}$$

The *NNFI* is based on the difference between the observed and the independence (null) model. The null model prohibits items from correlating (i.e., they are not interrelated), making it the worst-case model (Hooper et al., 2008, p. 55). Additionally, as *N* is not adjusted out, the *NNFI* is more sensitive to sample size than the *RMSEA*. However, like *RMSEA*, *NNFI* does account for model complexity. The current study derived *NNFI* values using the *C3* chi-square. All models were assessed according to recommended cutoffs of > .95, which reflects excellent fit, and > .90, which reflects adequate fit (Hu & Bentler, 1995, p. 84; Raykov & Marcoulides, 2006, p. 44).

Of note: the *NNFI* can be positively biased when latent factors are allowed to correlate (Hu & Bentler, 1999); however, the *NNFI* can also be underestimated when data are nonnormal (Raykov & Marcoulides, 2006, p. 63). Although underestimation has been minimized in some models using *N* > 250 (Hu & Bentler, 1999), which, with *n* = 920 the current study easily surpasses, that the *NNFI* was derived on the normality-corrected *C3* chi-square should have further ensured that underestimation was negligible. However, that the current study did allow for latent factors to correlate was taken into consideration when interpreting *NNFI* values.

Comparative fit index (CFI). The *CFI*, like the *NNFI*, can be underestimated when data are nonnormal unless *N* > 250 (Hu & Bentler, 1995, p. 85). However, this concern is again negligible in the current study because *n* = 920 and the *C3* chi-square was used. The *CFI* formula is as follows:

$$\mathrm{CFI} = \frac{(\chi^2_i - \mathrm{df}_i) - (\chi^2_{SB} - \mathrm{df}_{SB})}{(\chi^2_i - \mathrm{df}_i)}$$

The *CFI* assesses fit as the difference between the observed and the independence (null) models, but without adjusting *N* or complexity (df) out. The *CFI* can also be positively biased when latent factors are allowed to correlate (Hu & Bentler, 1999); this was taken into consideration when evaluating current study models. The current study evaluated model fitness with the recommended *CFI* cutoffs of > .90 for adequate fit, and > .95 for excellent fit (Hooper et al., 2008, p. 58).

Standardized root mean residual (SRMR). The SRMR reflects the difference between observed and hypothesized (expected) covariance matrix residuals, adjusted for the number of parameters (*p*) in the model:

$$\mathrm{SRMR} = \sqrt{\frac{\mathrm{SSr}_{jk}^2}{\left(\frac{p(p+1)}{2}\right)}}$$

As the root mean residual is based in part on the range of the ratings scale (which in the current study is 7-point Likert), standardization of the SRMR makes it useful regardless of number of rating categories. Per the SRMR formula, there is no adjustment made for sample size; therefore, it is sensitive to large *n* and will decrease as *N* increases (Hooper et al., 2008, p. 55). Additionally, the SRMR becomes smaller as number of parameters increases (Hooper et al., 2008, p. 55). Therefore, caution was exercised when interpreting the SRMR value given the current study's high *n* and rather complex model. Values < .08 are considered acceptable by convention (Hu & Bentler, 1999), whereas values < .05 are considered ideal (Hooper et al., 2008, p. 55; Hu & Bentler, 1999).

Goodness-of-fit of individual model parameters. Indices that can aid in identification of issues involving individual parameters include parameter significance tests, normalized (standardized) residuals, Q-plot of standardized residuals, and modification indices.

Parameter t-tests. LISREL conducts *t*-tests for parameters in the factor (lambda), latent error (psi), unattenuated factor correlations (phi), measurement error (theta-delta or theta epsilon), and latent means (tau) matrices (Byrne, 1989, p. 56). The *t* test statistics reflects the parameter's difference from 0, divided by its standard error (Byrne, 1989, p. 56). Therefore, models with lower standard errors have a better chance of yielding significant parameters. Values > 2 (commensurate with a *Z*-cutoff of 1.96 when distribution is two-tailed and $\alpha = .05$) in the current study were considered significant and therefore relevant to the model (Byrne, 1989, p. 56).

Normalized residuals. The normalized residual values reported in LISREL output reflect the number standard deviations a residual is from 0. Because these values have been standardized, they are analogous to a *Z*-score (Byrne, 1989, p. 57). As such, residuals in the current study that were > 2 were considered significant, and were examined for their contribution to a poorly fitting modeling. Specifically, several standardized residuals above +2 were seen as indicative of a model that was "underexplaining" the relations between variables and latent factors; i.e., more indicators were likely necessary. In contrast, several standardized residuals below −2.00 were indicative of an "overexplaining" model such that there were more variables in the model than necessary (Raykov & Marcoulides, 2006, p. 49). Models in the current study were considered good fits if the standardized median value was at or very near 0, and there were few significant standardized residuals in either direction. Models that had a great deal of residual error but improved after reconfiguration were considered better fitting if other fit indices concurred.

Normal probability (Q) plot. The Q-plot depicts the deviation of the residual distribution from normal. Normally distributed residuals are expected to fall along a right-slanted 45-degree line; undue deviations from that line are an indication of model misspecification (Byrne, 1989, p. 57). Q-plots in the current study were evaluated for standardized residuals' adherence to the line. Per convention, abrupt deviations in the upper and lower portions of the residual line were interpreted as indications that the model was misspecified (Byrne, 1989, p. 57), or that it included unnecessary parameters (Raykov & Marcoulides, 2006, p. 33). However, moderate departures from the line, if all other indices were feasible, were considered acceptable.

Modification indices. Modification indices (MI) are reported by LISREL for all fixed parameters in a specified model (Byrne, 1989, p. 57). These indices can facilitate change to the model to improve fit. However, MI recommendations should be considered in conjunction with theory to ensure that model fitness is feasible both statistically and substantively (Byrne, 1989, p. 57; Lei & Wu, 2007, p. 34). In the current study, the MI info was reviewed but not found to offer any theoretical or statistical suggestions of value.

SEM reliability. To verify the reliabilities found in the EPAF, structural equation modeling reliabilities for each latent factor were computed using the following formula:

$$\mathrm{REL}_{\mathrm{SEM}} = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \left(\sum_{i=1}^{n} \delta_i\right)^2}$$

Where lambda (λ) = factor loading, and δ = standardized error variance ($1 - \lambda$)

Reliabilities in the SEM context should be $\geq .70$ to indicate acceptable internal validity Memon, Rahman, Aziz, & Hazana, 2012, p. 11). Note that this formula can produce upwardly biased results when data are nonnormal (Basto & Pereira, 2012, p. 8). Therefore, SEM reliabilities are treated strictly as supporting evidence for factor reliabilities derived during PAF when such information is available.

SEM average variance extracted. The average variance extracted value in the SEM context reflects the average percent of variance explained by the items indicated by that factor (Garver & Mentzer, 1999, pp. 44–45). It is also a measure of convergent validity (Memon et al., 2012, p. 11). Because variance extraction values are not computed by LISREL, variance extraction per factor in the current study were computed by hand using the following formula:

$$VE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

Where lambda (λ) = factor loading and n = number of items.

Factors that account for ≥ 50% of total variance are considered reflective of internal validity, as values < .50 indicate that there is more variance unexplained than explained (Memon et al., 2012, p. 11).

Appendix D

Attempt to Replicate Using Pearson PM Correlations

To facilitate replication of the theoretical CRS model, the current study used, when appropriate and available, statistical methods and procedures patterned after or aligned with those used by Kulkofsky and Koh. Specific replication methods and procedures are described in conjunction with the applicable analyses. For example, because the Kulkofsky and Koh PAF was conducted in SPSS 15 (IBM Corp., 2006), by default, data are assumed to be continuous and normally distributed. The PAF produces a correlation matrix based on Pearson's Product-Moment (PMP) correlations, on which Kaiser extraction is performed. To best align with this analysis in the SEM context, the current study treated the response data as continuous, enabling LISREL to produce correlation (and covariance) matrices based on PPM correlations. Also, the estimation method chosen was maximum likelihood (ML) estimation. ML assumes that data are continuous and normally distributed and estimates model accordingly (Basto & Pereira, 2012, p. 4). As recommended in the literature, because ML was used, the model chi-square to report is the *C2*, which likewise assumes continuous, normally distributed data (Jöreskog, 2004, p. 2).

Results of the provisional EFA showed that the CRS-A did not replicate the Kulkofsky and Koh (2009) 7-function model. The first and perhaps most obvious possibility is that the CRS-A was adapted from items organized according to a hypothesized, but untested, 7-function model (Kulkofsky & Koh, 2009). Although theoretically sound (Kulkofsky and Koh, 2009, p. 458), no known evidence of its statistical viability has been published. Further, several other factors may have rendered replication problematic. Univariate datascreening indicated that CRS-A response data were negatively skewed and platykurtic. Multivariate normality diagnostics showed that Mardia's Index of Relative Multivariate Kurtosis was, at 1.494, below the *Z*-cutoff of 1.96 (for α = .05, two-tailed distribution) (Mardia, 1970); however, it was close to the 1.5 cutoff that recommends estimation methods and model chi-square that deal with multivariate nonnormality (Forero et al., 2009, p. 636). Other datascreening diagnostics indicated significant multivariate skew (Z = 119.34, p < .001) and kurtosis (Z = 52.92, p < .001). The condition number of 11.73 was below the cutoff of 15 (Cohen et al. 2004, p. 424) indicating that it was unlikely that issues with multicollinearity were contributing to poor model fit.

Other results of the provisional EFA indicated that factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were all significant and positive.[15] However, regression coefficients were unstable (low R^2 = .20; high R^2 = .87), signifying inconsistent reliabilities across items, and thus the model. The normal probability (Q) plot displayed a nearly horizontal residual line with breaks at both ends. Such a pattern suggests violations of normality, excess error, and/or the inclusion of unnecessary parameters (Raykov & Marcoulides, 2006, p. 33). The median standardized residual was .128, above the recommended value of 0. However, of particular interest was the fact that the standardized residual distribution was positively skewed, with the range of residuals running from −9.38 to +17.74, indicating that residuals extended far into the positive tail of the distribution. This was seen as evidence that the model was attempting to overexplain the construct, (Raykov & Marcoulides, 2006, p. 49), indicating that the model may include too many variables (items)[16].

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[15] Because the EFA was conducted from a structural equation modeling approach, results are evaluated as though the analysis was a confirmatory factor analysis (CFA). As such, not only the magnitude of loadings, but whether or not the loadings are significant (at $t \geq 2.00$), is relevant. Nonsignificant loadings, particularly in the lambda (factor) matrix, can be an indication that the model is misspecified (Byrne, 1989).

[16] Evidence of overextraction and/or inclusion of unessential items manifests differently depending the type of analysis. Because all included items will load somewhere, and their mere presence will increase reliability, a variety of results are used to determine if items are truly essential. See section on “A Different Approach” for details.

Per the *C2* model chi-square, the provisional EFA model demonstrated an adequate to poor fit, $\chi^2(758) = 6009.20$, $p < .001$. Given chi-square's sensitivity to large *n*, the significance of this test was likely due to the sample being overpowered ($n = 921$). The *RMSEA*, based on the *C2* chi-square was .087, slightly above the upper cutoff of .08 to indicate adequate-to-poor model fit (Raykov & Marcoulides, 2006, pp. 46–47). The SRMR of .0852 was slightly above its recommended cutoff of .08 (Hu & Bentler, 1999, p. 24) to indicate estimation error in the model. Likewise, the χ^2/df ratio, at 7.93, was well above the "adequate" cutoff of 5.0 (Byrnes, 1989, p. 55). As such, although somewhat mixed, thus the evidence suggests a poor fit. Although both the *NNFI* and *CFI* were above the .95 cutoff (.980 and .982, respectively), implying excellent fit, neither of these indices adjust for large sample sizes, and are susceptible to inflation when latents are allowed to correlate. This further recommended that the 7-function model established by Kulkofsky and Koh was not replicable with the current dataset collected with a modified instrument.

SEM reliability calculations indicated that all factors demonstrated internal validity by surpassing the .70 cutoff: Conversation = .86; Relationship Maintenance = .93; Behavioral Control = .90; Teaching/Problem Solving = .88; Emotion Regulation = .94; Self = .88; and Cognitive Skills = .87. Given that the SEM reliability calculation can lead to biased results when data are nonnormal (Basto & Pereira, 2012, p. 8), these results may even be inflated. This is especially possible given that the estimation method (ML) by which the factor loadings were derived biases results when data are nonnormally distributed and not naturally continuous (Hu & Bentler, 1999; Jöreskog, 2004). As the provisional EFA was conducted in lieu of factor analysis, there are no factor analysis-derived reliabilities against which to compare these results for accuracy and practicability.

Per the average variance extraction calculations, the amount of variance accounted for by each function associated with each factor by the model also exceeded the minimum recommended value of 50%: Conversation = 55.80%; Relationship Maintenance = 54.97%; Behavioral Control = 75.37; Teaching, Problem Solving = 59.32%; Emotion Regulation = 82.77%; Self = 77.2%; and Cognitive Skills = 75.04%. However, adding items to a model will always lead to an increase, and never a decrease, of variance explained whether or not those variables theoretically belong (Nathans, Oswald, & Nimon, 2012, p. 8). Although this could be premised on sampling items from the same pool as the items already included, or due to method, that all factors are accounting for a substantial amount of variance is most likely due to the model is overpowered by superfluous items (Cohen et al., 2004; Tabachnick & Fidell, 2007).

Results of the follow-up CFA mirrored those of the provisional EFA, substantiating concerns of the replicability of the theoretical 7-function model with adult samples. However, the consistency in results across the two SEM analyses did imply sample equivalency. Further, for those aspects of the provisional EFA and CFA configurations that did perform well, the consistency across analyses could be evidence that CRS-A was capable of tapping into the true adult AM functions. As was the case with the provisional EFA, CFA univariate normality diagnostics showed negative skew and platykurtosis. Per MV normality diagnostics, Mardia's Index of Relative Multivariate Kurtosis was , at a value of 1.495, below significant cutoff of 1.96 (Mardia, 1970). However the data showed significant multivariate skew (Z = 121.28, $p < .001$) and kurtosis (Z = 52.91, $p < .001$). The condition number (11.97) was below the 15 cutoff to suggest no issues of multicollinearity. Per the CFA, factor loadings (lambda matrix), disturbances (psi matrix), and factor variances (theta-delta matrix) were all significant and positive. As with the EFA, CFA regression coefficients were unstable (low R^2 = .20; high R^2 =

.88). The Standardized Root Mean Residual for the CFA was .082 (optimal < .08), indicative of error (Hu & Bentler, 1999, p. 24). The normal probability (Q) plot was, as was the case with the EFA, horizontal with changes in direction on both ends, indicating violations of normality, excess error and/or the inclusion of unnecessary parameters (Raykov & Marcoulides, 2006, p. 33). The median standardized residual was .280, with slightly less positive skew than in the EFA (range from −11.48 to +16.77); however, 82 standardized residuals (10%) remained < −2.00 and 180 (21%) > +2.00, indicating that the majority of residuals stretched into the distribution's positive tail. As with the EFA, residuals results suggest that too many variables were included in the model (Raykov & Marcoulides, 2006, p. 49).

Fit indices for the CFA further confirmed poor model fit. Per the *C2* test statistic, $\chi^2(758) = 5866.62.83$, $p < .001$. The *RMSEA*, at .082, still exceeded the upper cutoff of .08. The χ^2/df ratio was 7.74, still above the "adequate to poor" cutoff of 5.0 (Byrnes, 1989, p. 55). Again, both the *NNFI* (.98) and the *CFI* (.98) indicated excellent fit, whereas the SRMR was again above the optimal .08 cutoff at .084.

Appendix E

The R-Approach to Factor Analysis

The following details the changes adopted at the measurement and estimation levels, and the changes in approach taken to establish an AM functions model for adult samples.

Measurement Level

It is unknown if the Kulkofsky and Koh (2009) dataset demonstrated nonnormal properties, as no datascreening results of any kind were reported. This makes it difficult for replication researchers to determine if analyses conducted by Kulkofsky and Koh were affected by violations of it. What is known is that the CRS data was ordinal in nature, but treated as though it were continuous. There are claims in the literature that Likert-type data may, when normally or near-normally distributed, behave much like continuous data (Basto & Pereira, 2012, p. 4). However, self-report respondents tend favor the high end of frequency scales, so ordinal data are typically negatively skewed and kurtotic (O'Connor, 2000, p. 398). Treating nonnormal data as continuous can become problematic if the nonnormality is sufficient to bias results. However, regardless of normality, a number of sources warn that treating ordinal data as interval/ratio often leads to specious conclusions (Basto & Pereira, 2012, p. 4; Bernstein & Teng, 1989; Gilley & Uhlig, 1993; Stevens, 1946). Negatively skewed data can lead to improper estimates of r values[17]. Inflated r values can imply stronger item relations than exist, and can spuriously boost reliability estimates based on r, such as Cronbach's α alpha (Basto & Pereira, 2012, p. 4). Further, factor extraction based on r can falsely imply multidimensionality (Basto & Pereira, 2012, p. 4; Bernstein, Garbin, & Teng, 1988). This is of concern in the current study because

[17] This is stated with the caveat that individual items can be seriously flawed, therefore estimating the structure of conceptual domains from relations among items was done with this in mind.

standardized residuals and the Q-plots of the provisional EFA (and follow-up CFA) suggested that the model included superfluous items. As for kurtosis, when data are leptokurtic and treated as continuous, standard errors are underestimated and results biased. When data are platykurtic, standard errors are overestimated, which negatively biases results (West et al., 1995, p. 63). This was also a concern for the current study, as mot items were not only negatively UV and MV skewed and UV and MV platykurtic, but significantly so[18]. As such, analyses took the ordinal and nonnormal nature of the CRS-A data into account.

Estimation Method

The estimation method used in the provisional EFA (and follow-up CFA) was maximum likelihood (ML). When data are multivariate normal and treated as continuous, ML is the most powerful and unbiased estimation method (Mîndrilă, 2010, p. 60). If data are multivariate normal but treated as ordinal, then ML estimation is less than optimal, but still recommended (Mîndrilă, 2010, p. 61). However, when data are ordinal and multivariate nonnormal, ML is inappropriate unless data are transformed and/or outliers are removed to achieve normality (Gao et al., 2008, p. 116)[19]. Additionally, if data are multivariate platykurtic—as the CRS-A data were—ML will overestimate standard errors, resulting not only in biased χ^2 test statistics, but biased fit indices when derived from the biased chi-square (Hu & Bentler, 1999; Jöreskog, 2004).

[18] To be clear, results showed that, when considering the dataset as a whole, data were significantly UV and MV negatively skewed and platykurtic. Therefore data were managed to address these issues. However, a proportion of individual items were not significantly problematic, but were too small in number to impact overall results. But it is noted that correlations negatively skewed items and items that are normally distributed or near normally distributed result in underestimated PPM coefficients.

[19] As was discussed in the Datascreening subsection, neither transformations nor the removal of outliers were productive options in the current study.

The most appropriate estimation method for CFAs given the ordinal and nonnormal nature CRS-A data is robust unweighted least squares (RULS) (Forero et al., 2009, p. 639).[20] RULS is a “robust” estimation in that standard errors, which are impacted by multivariate nonnormality, are (made less sensitive to violations of normality) before being applied to chi-square computations and other relevant estimates (Jöreskog & Sörbom, 2012, p. 9) RULS has also been shown to handle bias in a model due to the oblique nature of factors (Jöreskog & Sörbom, 1989, pp. 156162; Wothke, p. 266). This was important to the current study for three reasons: (1) factors were oblique to be consistent with the procedure established by Kulkofsky and Koh (2009, p. 463); (2) it is considered theoretically more appropriate in the behavioral sciences to allow factors to correlate versus treating them as orthogonal (for a detailed discussion on the rationale of the second point, see Fabrigar, Wegener, MacCullum, & Stanhan, 1999); (3) even if factors can be explained theoretically as orthogonal, it is considered good statistical practice to allow the factors to correlate (Worthington, 2006, p. 833)

EFA as Principal Axis Factoring with Ordinal Variables Using R-Factor

The current analysis began with a principal axis factor (PAF) to derive a statistically supported model on which to base a validating confirmatory factor analysis (CFA) performed using structural equation modeling (SEM). Because the EPAF was run on untested adapted items (CRS-A) with an untested sample (adults), the PAF was considered exploratory (hence, EPAF). Validating the EPAF with a structural equation model CFA is recommended to overcome a couple of insurmountable limitations of EFAs (e.g., exploratory PAFs) (Bryant & Yarnold, 1995,

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[20] Another estimation method recommended for multivariate nonnormal data is the asymptotically free distribution (AFD) estimation (Browne, 1984). However, ADF is not recommended for models with more than 20 observed variables (CRS-A has 36) and samples less than 2500 (largest CRS-A CFA group n = 921) (Hardy & Bryman, 2004, p. 443; West, Finch, & Curran, 1995, p. 65).

p. 111). One limitation is that factor analysis is based on *correlation* matrices, whereas an SEM CFA is computed from *covariance* matrices. (Bryant & Yarnold, 1995, p. 111). Covariance matrices (which consider both on-diagonal or variance information, and off-diagonal or covariance information) provide much more information about the interrelationships between variables and differences between factors than can be obtained from a correlation matrix (which considers only on-diagonal information). As a result, EFA solutions depict a less detailed picture, so should be treated as a starting point versus a final product (Bryant & Yarnold, 1995, p. 111). That Kulkofsky and Koh (2009) validated neither their theoretical model nor PAF-derived model with a SEM CFA was of concern. Thus the structure recommended by the current study's EPAF informed the CFA setup, but it was the CFA results that ultimately directed and dictated the final model.

The exploratory PAF (EPAF) thus became the current study's foundational analysis for testing Hypothesis 1. Preceding the results of the EPAF below are details on the methodology and procedures used.

R-Factor

Because the CRS-A data was ordinal, the current study sought a statistical analysis program that, unlike SPSS (IBM Corp., 2012), allowed for the creation of the correlation matrices that underlie PAF analyses that were not dependent on Pearson's Product-Moment (PPM) correlations. Therefore, the current study's EPAF was run using R-Factor (Basto, 2012). R-Factor is a relatively new software program that integrates SPSS with the R Project Statistical Package (R Development Team, 2008). One of the many advantages of R-Factor is that it offers the point-and-click ease of SPSS with the myriad sophisticated analyses available through R. Also, R-Factor was specifically designed for factor analysis with ordinal data (Basto & Pereira, 2012, p. 1). It allows for the computation of *heterochoric correlations*. Heterochoric correlations integrate those correlation types essential to factor analyses and structural equation modeling: polychoric (ordinal variables to ordinal variables; i.e., item to item for correlation and covariance matrices), polyserial (ordinal to continuous; i.e., item to latent factor), and PPM (continuous to continuous; i.e., for correlations between oblique latent factors).

Number of factors to retain. Another major advantage of R-Factor is that it provides diagnostics on which to decide the number of factors to retain. This was important to the current study given that the results of the provisional EFA (and follow-up CFA) suggested the presence of too many items (and thus potentially too many factors). Although the Kulkofsky and Koh (2009) data was also ordinal, because their PAF was run in SPSS, it was by default relegated to a PPM correlation matrix and the Kaiser method of extraction (Basto & Pereira, 2012, p. 5). The problems associated with using PPM correlations on ordinal data—particularly when nonnormal—has been fully discussed elsewhere in this manuscript. As for extraction methods, they “extract” out the number of factors in a model by evaluating variance in one of two ways (Basto & Pereira, 2012, p. 5). For PAF, extraction is based on the amount of *shared* variance between items. Items that share the most variance are thought to be underlain by the same latent dimension, and are thus grouped within the same factor. Another popular factor analysis method is principal components analysis (PCA). PCA extraction is based on *total* variance, whereby items that account for the greatest amount of explained variance are grouped. The item groupings in a PCA are called components or eigenvectors. The first component always reflects the greatest amount of variance explained, whereas subsequent components explain increasing less remaining model variance (Basto & Pereira, 2012, p. 5). The Kaiser method by design ranks the values of the components, or “eigenvalues,” from high to low; values greater than 1.0 are considered essential factors to the model (Basto & Pereira, 2012, p. 5). The Kaiser method is therefore ideal for PCA, but for PAF can produce misleading results (Basto & Pereira, 2012, p. 5). This is especially true for models featuring less than "optimal" conditions; i.e., models with ordinal variables, nonnormally distributed data, > 30 items, communalities[21] < .70 if samples < 250; communalities < .60 if samples > 250 (Bryant & Yarnold, 1995, p. 106; Worthington, 2006, p. 832). In such cases, the Kaiser method tends to "overextract" (overestimates the number of factors relevant to the model) (Basto & Pereira, 2012, p. 5; Costello & Osbourne, 2005; Lance, Butts, & Michels, 2006; Zwick & Velicer, 1986). The Kulkofsky and Koh model possessed none of the "optimal" criteria, thus their PAF likely reflected overextraction. This, coupled with evidence from the provisional EFA that the 7-funtion model was "overexplaining" the construct, indicated that a more stringent and sophisticated PAF approach was needed to discern the true number of AM functions on which to base a CFA.

R-Factor reports indices and graphic comparisons of several extraction procedures not available in SPSS. These estimates are meant to aid researchers in determining the number of factors to retain from a statistical perspective. For the current study, results of extraction diagnostics were used in conjunction with PAF factor loading patterns and strengths. Resultant models that were statistically but not theoretically feasible were disregarded. What follows are brief descriptions of the extraction diagnostics provided by R-Factor that were used by the current study.

Diagnostic descriptions and procedures. The parallel analysis (PA) procedure was one of two number-of-factor estimators of interest to the current study. PA generates a normally

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[21] Communalities reflect the amount of variance an items shares with all other variables in the model. A communality is equal to (1 – uniqueness), uniqueness being the amount of variance in the model explained by that item's variance alone.

distributed random dataset with the same number of variables and cases as the original dataset, so that extraction is not biased by nonnormal data (Basto & Pereira, 2012, p. 5). When data are ordinal and the PA is set to evaluate polychoric correlations, the diagnostic reports a mean eigenvalue that has been shown to have a high degree of accuracy (Courtney, 2013, p. 4).

Similar to PA is Velicer's minimum average partial (MAP). The difference between the PA and Velicer's MAP is that the latter retains factors only when correlation matrix variance reflects systematic (nonrandom) variance (Basto & Pereira, 2012, p. 5). Velicer's MAP has been shown to be an accurate estimation method; however, it may underestimate when factor loadings are low, or when there are only a few items loading on a factor (Basto & Pereira, 2012, p. 6; Zwick & Velicer, 1986). Of importance to the current study, Velicer's MAP is thought to yield the most accurate estimations when for ordinal variables when data the underlying correlation matrix is polychoric. In such models, the squared-average partial result (versus the fourth power result, both of which are reported by R-Factor by default) is the one interpreted (Basto & Pereira, 2012, p. 5). The Velicer's MAP diagnostic provides a minimum average partial test, which recommends the fewest factors to be retained before risking loss of explanatory model variance (Courtney, 2013, p. 9). The Velicer's MAP diagnostic also provides a table of squared average partial correlations per number of possible factors The number of factors to retain occur at the number of factors at which squared average partial correlations no longer decline, but plateau or increase (Courtney, 2013, p. 9).

The fit to comparison data (CD) plot depicts an eigenvalue of the root mean square residual (RMSR) of tabulated data to show improvement between factor solutions. Like the *NNFI* used in structural equation modeling, the CD reflects the difference (error, residual) between the observed data and the worst-case model (MacCallum, 2009, p. 130). The plot is accompanied by a significance test of RMSR eigenvalues for each possible number of factors. The final significant RMSR eigenvalue in the model is the number to be retained.

Finally, R-Factor diagnostics provide two other values against which to make number-of-factor judgments: the optimal coordinate (OC) and the acceleration factor (AF). Both were designed as alternatives to the default scree test provided by SPSS (Basto & Pereira, 2012, p. 5). However, a recommended version of either have been established, so OC and AF results will be disregarded in the current study (Courtney, 2013, p. 11).

Results: Number of factors to retain. The current study EPAF used a heterochoric (polychoric for item-item relations) correlation matrix. The model included all 41 CRS-A variables and all cases (n = 921; one random half of the full dataset). Although the current study met more "optimal conditions" criteria (sample > 250) than were met in the Kulkofsky and Koh PAF, there was a concern that Kaiser (reported as mean eigenvalue) would overextract. Extraction diagnostic results showed that the mean eigenvalue was 7 and the PA was 5. Figure 4 depicts the eigenvalue plot. Because these values differ, the optimal number of factors is somewhere between 5–7 (Basto & Pereira, 2012, pp. 5–7). Per Velicer's minimum average partial test, the squared MAP value indicates that the minimum number of factors to retain is six. Results of the Velicer's squared average partial correlations were as follows: 0 = .196; 1 = .025; 2 = .021; 3 = .019; 4 = .016; 5 = .015; 6 = .013; 7 = .013; 8 = .013; 9 = .013; 10 = .013, 11 = .014. Because values plateau at factor seven, six appears to be the optimal number of factors to retain.

The fit to comparison data also indicated that the optimal number of factors to retain was six. Results showed that moving from six factors (p < .001) to seven resulted in a nonsignificant improvement (p = .935). The fit-to-comparison plot (Figure 5) depicts the CD diagnostic conclusion that improvement fails to occur beyond six factors.

PAF in R-Factor

Because PAF in R-Factor offers options relevant to models using ordinal variables, the sections below detail descriptions of those options (rotation methods, tests of sample adequacy, and reliability) followed by results of the PAFs conducted for the current study.

Rotation methods, tests of sample adequacy, and reliability. R-Factor offers myriad rotation methods for both orthogonal and oblique solutions. Rotation methods facilitate the interpretation of PAF results without affecting goodness-of-fit (Basto & Pereira, 2012, p. 3). Because results of the provisional EFA implied an "overexplained" model, the current study chose Quartermax (oblique) rotation for its ability to reduce the number of latent factors required to "explain" each variable (Basto & Pereira, 2012, p. 3)[22]. Oblique rotation methods require that the rotation parameter of delta (δ) be set. Delta reflects degree of allowed "obliqueness" (intercorrelation of factors), whereby $\delta = 0$ (aka Quartermin) provides as oblique a rotation as possible, and $\delta > 0$ provides increasingly more relaxed obliqueness (Basto & Pereira, 2012, p. 3). The current study set $\delta = 0$. However, to ensure that the Quartermax rotation was not overcorrecting for an "overexplained" model, results of the final PAF were verified with Varimax orthogonal (no intercorrelation of factors). Varimax is considered the rotation method most likely to return a parsimonious solution while effectively differentiating between factors (Basto & Pereira, 2012, p. 3). However, the exclusive use of Varimax rotation, which is designed to yield factor correlations of 0, would have precluded the computation of the factor correlations

[22] Because R-Factor offers multiple rotation methods beyond those included in SPSS, several of which are appropriate for the modeling done in the current study, a number of PAFs using various rotation methods were conducted to ensure that the Quartermin-Q was not returning results overly biased in favor of any one configuration. Because those analyses were post-hoc and for comparison purposes only, those results are not reported herein.

essential to both the understanding of item polarity and the interpretation of trait-level past-talk behaviors. Results of analyses using Quartermax and Varimax analyses are detailed in the *Results: PAF* subsection below.

PAF in R-Factor also reports the following sample adequacy indices and graphs, all of which are not provided by SPSS (IBM Corp., 2012). To determine whether the correlation matrix on which the factor analysis is based is the identity matrix (a correlation matrix that is also the identity matrix is thought to be most fit for factor analysis), three chi-square tests are produced. Nonsignificant chi-squares signify that the correlation matrix and identity matrix are equivalent. Thus, *n. s.* results indicate that the samples are adequate for PAF (Basto & Pereira, 2012, p. 2). However, the three chi-square tests—Bartlett's Test of Sphericity, Jennrich test, and Steiger test— are, like all chi-square tests, overly sensitive to sample size, so are prone to null rejection when *n* is large (Basto & Pereira, 2012, p. 2). Therefore, a better measure of sample adequacy with large samples is the Kaiser Meyer Olkins (*KMO*). Values of the *KMO* range from 0–1.0, with values > .60 indicating that a sample is suitable for factor analysis. (Hutcheson & Sofroniou, 1999).

R-Factor also produces tests of multivariate normality and a model root mean square residual (RMSR). Neither are provided by SPSS (IBM Corp., 2012). These values are derived using the same procedures as those used in structural equation modeling (see descriptions in the Datascreening and Fit Indices subsections above). Additionally, R-Factor provides an index of model quality called the Goodness of Fit (GFI) index. The *GFI*, like the *NNFI* and *CFI* reflect the proportion of correlations that are explained by the model, with values > .95 indicative of good fit (Basto & Pereira, 2012, p. 7). Like the *NNFI*, it is adjusted for model complexity. Because the R-Factor *GFI* is based on ULS estimation, this index was of particular interest to the current study. For comparison purposes, also reported is a ML-based *GFI*; one *GFI* is higher than the other can indicate which estimation method is more advantageous given the sample data.

The R-Factor PAF also provides the traditional diagnostics for determining number of factors to extract. By convention, factors with eigenvalues > 1.0 are considered relevant to the model (Bryant & Yarnold, 1995, p. 128). In conjunction with eigenvalues > 1.0, the total amount of variance in the model should be > 60% (Reddy & Acharyulu, 2009, p. 335). Models that account for < 60% total variance when eigenvalues < 1.0 are not included are indicative of other issues with the model (Reddy & Acharyulu, 2009, p. 335). The scree plot depicts eigenvalues per factor in graphic form. The number of factors to retain occur at the "elbow" of the plotted eigenvalues. It is common for scree plots to overestimate the optimal number of factors to retain as reported in the eigenvalue-per-factor table (Reddy & Acharyulu, 2009, p. 335).

Finally, R-Factor provides three reliability measures to compare to Cronbach's alpha (α), which is the sole reliability measure reported in SPSS (IBM Corp., 2012). Reliability is an index internal validity; it reflects a scale's ability to measure the construct it is designed to measure. That is, the more reliable the scale, the more likely it will yield consistent results when administered to other samples (Basto & Pereira, 2012, p. 7). Although Cronbach's α is the most widely reported reliability measure, it is can be upwardly biased when ordinal are treated as continuous and are negatively skewed. If Cronbach's α is derived on ordinal-based polychoric or heterochoric correlations, which are less sensitive to bias due to skew, α can under report reliability. Additionally, Cronbach's α assumes unidimensionality; i.e., it assumes that all items are underlain by a single latent construct (Basto & Pereira, 2012, p. 8). This was of concern in the current study, given that the Pearson's r assumptions that data be continuous and normally distributed had been violated, and that the Cronbach's α requirement of unidimensionality was unfeasible (as it was for the Kulkofsky and Koh model, although not reported as such). One of R-Factor's reliability options is Armor's reliability theta (θ)—a reliability measure most relevant in a multidimensional PCA context when using continuous variables; an ordinal-reliability θ, and an ordinal-reliability α. That the current study was running a multidimensional EPAF using ordinal-level data, the latter reliability measure was of particularly interest. Also important was the fact that the ordinal-reliability α has been found to be appropriate when data are nonnormal (Basto & Pereira, 2012, p. 9).

Appendix F

Summary of Multigroup Invariance Tests

The following summarizes the incremental multigroup models used by the current study to test the invariance of the CRS-A across time (test-retest), gender, and ethnicity. The protocol is based on that recommended by Milfont & Fischer (2012).

Model 1: Configural Invariance

Configural invariance is the first of the *measurement* invariance models; i.e., nested models that test the relation between observed variables (items) and latent variables (factors). Configural invariance is tested by holding constant the factor structure across groups. Invariance of the configural model indicates that respondents across groups are in agreement as to the meaning of the construct. The configural model serves as the baseline against which the subsequent measurement, and optionally the structural, invariance models are compared.

Model 2: Metric Invariance

Also called *structural* or *factor loading* invariance, this is the second of the measurement invariance tests. Metric invariance is tested by holding all factor loadings to be equivalent across groups. Factor invariance indicates that respondents rate items in the same way. As factor invariance can be difficult to obtain, *partial metric* invariance—whereby as few as two factors are constrained—is often incorporated. However, the exploratory nature of the current study's MGCFAs, and thus lack of guidance from the empirical or theoretical literature, precluded the use of partial factor invariance in the current study.

Model 3: Scalar Invariance

The third measurement invariance test is also known as *intercept* invariance. Scalar invariance is tested by constraining all item intercepts to be equal across groups. Models that demonstrate scalar invariance indicate that a respondent's latent factor score is indicated by his or her item score, regardless of group membership. As scalar invariance is also often difficult to obtain, *partial scalar* invariance is also commonly used, whereby at least two loadings and intercepts must be constrained (Byrne, 1989). But again, the exploratory nature of the current study cautioned against partial invariance techniques to preclude conclusions that were largely data driven and theoretically unsubstantiated. Of note, the test of scalar invariance is often considered the last mandatory test, with all subsequent tests being optional. Further, scalar invariance is widely considered a requirement to accepting factor mean invariance, even if tests of factor means on their own suggest invariance (Byrne, 1989).

Model 4: Error Variance Invariance

Error variance invariance is the fourth measurement invariance test. It is commonly considered optional, but was included in the current study, an objective of which was to reveal and explain the true set of adult AM functions. It is tested by constraining the error variances to be equal across groups. A model that demonstrates error variance invariance indicates that items feature the same levels of measurement error across groups.

Model 5: Factor Variance Invariance

Factor variance invariance is the first of the *structural* invariance tests. Structural invariance tests examine the properties of the latent variables (factors). The models tested with structural invariance tests need not be nested; i.e., results of these models can be compared to the results of the scalar invariance model directly. Factor variance invariance is tested by holding as equal all factor variances across groups. A model found to be favor variance invariant indicates that the range of scores within a latent variable (factor) does not vary across groups.

Model 6: Factor Covariance Invariance

This is the second of the structural invariance tests and also need not be nested. It is tested by holding all factor covariances to be equal across groups. Obtaining factor covariance invariance indicates that all latent variables have the same interrelationships across groups.

Model 7: Factor Mean Invariance

The last of the structural invariance tests, models that show invariance across factor means indicate that groups differ across factor constructs. It is tested by constraining the factor means to be equal across groups. However, most sources require that factor mean invariance be claimed only when the model has shown evidence of scalar invariance (Byrne, 1989).

Table 1

General Demographic Information

		Frequency (%)
Gender		
	Males	529 (28.7%)
	Females	1305 (70.9%)
	Subtotal	**1834 (99.6%)**
	Declined to answer	7 (.4%)
Ethnicity		
	Caucasian	771 (41.9%)
	African-American/Black	451 (24.5%)
	Arab	249 (13.5%)
	Asian	171 (9.3%)
	Hispanic	60 (3.3%)
	Multiracial	63 (3.4%)
	Native American	6 (.3%)
	Native Hawaiian/Pacific Islander	4 (.2%)
	Other	39 (2.1%)
	Subtotal	**1814 (98.5%)**
	Declined to answer	27 (1.5%)
Over 18		
	Yes	1811 (98.4%)
	No	22 (22 (1.2%)
	Subtotal	**1833 (99.6%)**
	Declined to answer	8 (.4%)

Table 2

Theoretical CRS Items with Their Matching Functions (CRS version from which CRS-A Items Were Adapted)

Social Functions

Conversation

1. Entertain my child
2. Entertain myself with stories about my child
3. Entertain others with stories about my child
4. Share my child experiences with other members of our family
5. Have fun

Relationship Maintenance

6. Bond with my child
7. Help me understand my child better
8. Understand how my child feels about an event
19. Remind my child that s/he is loved
10. Help my child feel close to family members
11. Help my child understand other family members better
12. Help my child remember family members
13. Repair relations between my child and his/her friends
14. Help dissolve disputes between my child and his/her friends
15. Help my child understand his/her friends better
16. Help my child feel close to his/her friends

Directive Functions

Behavioral Control

17. Remind my child of the consequences of negative behavior
18. Teach my child moral lessons
19. Teach my child how s/he should behave

Teaching/Problem Solving

20. Prepare my child for an upcoming event
21. Help my child problem-solve

Emotion Regulation

22. Help my child feel better when s/he is experiencing negative emotions
23. Teach my child appropriate emotional responses
24. Teach my child how to control his/her emotions
25. Help my child cope with stressful or upsetting situations
26. Help my child make sense of his or her emotions
27. Help my child process an emotional experience
28. Help my child understand how others feel

Self Functions

29. Help my child feel good about him or herself
30. Build my child's sense of self
31. Build my child's unique individual identity
32. Help my child understand that s/he is part of a larger group
33. Tell my child what s/he was like when s/he was younger

Cognitive Skills

34. See how far back my child can remember

35. Test my child's memory
36. Teach my child how to remember
37. Help my child understand the concept of time
38. Develop my child's language skills

Note: The instrument is introduced with the instructions, "We are interested in conversations that you have with your child about events that your child has previously experienced. We refer to these conversations as *past talk*. Past talk may include events that you and your child experienced together as well as events that your child may have experienced but you did not. Please keep past talk conversations in mind when answering the following questions." Two general questions are then asked of the parent: "Do you ever engage in past talk with your child?" (Yes/No) and "How often do you engage in past talk with your child?", which is rated on a 7-point Likert-type scale with *1 = very rarely* and *7 = very often*. Items are in response to the stem statement, "I engage in past talk with my child in order to…" Responses to the CRS are rated on a 7-point Likert-type scale (*1 = almost never; 2 = rarely; 3 = seldom; 4 = occasionally; 5 = sometimes; 6 = often; 7 = very often*) (Kulkofsky & Koh, 2009).

Table 3

CRS Items, Their Theoretical (THR) AM Functions, Their Validated (VAL) AM Functions, and Their Validated Factor Loadings

Factor and items	THR	VAL	Loading
Give us something to talk about	CON	--	<.40
Entertain my child	CON	CON	.64
Entertain myself with stories about my child	CON	CON	.75
Entertain others with stories about my child	CON	CON	.81
Share my child experiences with other members of our family	CON	CON	.73
Have fun	CON	CON	.62
Bond with my child	RM	POS	.68
Help me understand my child better	RM	POS	.67
Understand how my child feels about an event*	RM	POS	.41
Remind my child that he/she is loved	RM	POS	.48
Help my child feel close to family members	RM	ISRO	.67
Help my child understand family members better	RM	ISRO	.79
Help my child remember family members	RM	ISRO	.65
Repair relations between my child and his/her friends*	RM	PEER	.75
Help dissolve disputes between child and his/her friends	RM	PEER	.89
Help my child understand his/her friends better	RM	PEER	.67
Help child feel close to his/her friends	RM	ISRO	.62
Remind my child of the consequences of negative behavior	BC	DIR	.76
Teach my child moral lessons	BC	DIR	.71
Teach my child how he/she should behave	BC	DIR	.78
Explain ongoing activities	TPS	ER	.34
Prepare my child for an upcoming event	TPS	DIR	.41
Help my child problem-solve	TPS	DIR	.69
Help my child feel better when he/she is experiencing negative emotions	ER	POS	.57
Teach my child appropriate emotional responses	ER	ER	.82
Teach my child how to control his/her emotions	ER	DIR	.71
Help my child cope with stressful or upsetting situations*	ER	ER	.77
Help my child make sense of his or her emotions	ER	ER	.57
Help my child process and emotional experience	ER	ER	.73
Help my child understand how others feel	ER	ER	.76
Help my child feel good about him or herself	SELF	POS	.67
Build my child's sense of self	SELF	POS	.63
Build my child's unique sense of individual identity*	SELF	ISRO	.61
Help my child understand that he/she is a part of a larger group	SELF	ISRO	.74
Tell my child what he/she was like when he/she was younger	SELF	ISRO	.45
See how far back my child can remember	COG	COG	.78
Test my child's memory	COG	COG	.86
Teach my child how to remember	COG	COG	.84
Help my child understand the concept of time	COG	ISRO	.55
Develop my child's language skills	COG	COG	.49

Note: Loadings derived using Promax, $k = 2$; data as continuous. Theoretical CRS functions: CON = Conversation; PT = Perspective-Taking; RM = Relationship Maintenance; BC = Behavioral Control; TPS = Teaching/Problem-Solving; ER = Emotion Regulation; SELF = Self; and COG = Cognitive Skills. Validated CRS functions: DIR = Directive; POS = Positive Emotionality; PEER = Peer Relations; ISRO = Individual Self in Relation to Others. Items marked with (*) featured slightly different wording in the VAL version from what appears above.

Table 4

Adapted CRS Items with Their Matching Functions as Administered in the Current Study

Social Functions

Conversation

1. Give us something to talk about
2. Entertain myself with stories of past experiences
3. Entertain others with stories of past experiences
4. Share my experiences with others
5. Have fun

Relationship Maintenance

6. Bond with others
7. Help me understand others
8. Understand how others feel about an event
9. Remind myself or another that I am/he or she is loved
10. Help myself feel close to family members
11. Help myself understand family members better
12. Help myself remember friends or family members
13. Repair relations between myself and friends or family members
14. Help resolve disputes between myself and friends or family
15. Help myself understand friends better
16. Help myself feel close to friends

Directive Functions

Behavioral Control

17. Emphasize the consequences of negative behavior
18. Clarify moral lessons
19. Bring to mind appropriate or preferred behavior

Teaching/Problem Solving

20. Explain ongoing activities
21. Prepare myself or others for an upcoming event
22. Help myself or others problem-solve
23. So that I or another avoids repeating a past mistake at some later date
24. To see how my or another's strengths can help solve a present problem

Emotion Regulation

25. Help lessen my or another's negative emotions
26. Emphasize or clarify appropriate emotional responses
27. Help me or another control emotions
28. Help me or another cope with stressful or upsetting situations
29. Help me make sense of my or another's emotions
30. Help me or another process an emotional experience
31. Help me or another to understand how others feel

Self Functions

32. Help me feel good about myself
33. Build or maintain my sense of self
34. Build a unique individual identity for myself
35. Help me to feel or recognize that I am part of a larger group

36. Remind myself of what I was like when I was younger

Cognitive Skills

37. See how far back I can remember
38. Test my memory
39. Keep my memory and recall sharp
40. Remind myself of how far I've come and all the experiences I've had
41. Improve my ability to convey my past experiences and memories to others

Note: The adapted instrument is introduced with the instructions, "We are interested in how and why people engage in *past talk*. Past talk is conversation about events that you have experienced either with the person(s) you are speaking to or that you have experienced but your conversational partner(s) have not. Please keep past talk conversations in mind when answering the following questions." Two general questions are then asked: "Do you engage in past talk?" (Yes/No) and "How often do you engage in past talk?," which is rated on a 7-point Likert-type scale (*1 = almost never; 2 = rarely; 3 = seldom; 4 = occasionally; 5 = sometimes; 6 = often; 7 = very often*). Items are in response to the stem statement, "I engage in past talk with myself and/or others in order to…" Responses to the CRS-A are rated on a 7-point Likert-type scale (*1 = never; 2 = rarely; 3 = seldom; 4 = occasionally; 5 = sometimes; 6 = often; 7 = very often*) (Kulkofsky & Koh, 2009). Items 23 & 24 are adapted from the Problem-Solving subscale of the Reminiscence Functions Scale (Robitaille, Cappeliez, Coulombe, & Webster, 2010; Webster, 1997).

Table 5

TALE Items with Their Matching Functions

Self-Continuity Function Subscale

1. When I want to feel that I am the same person I was before.
3. When I am concerned about whether I am still the same type of person that I was earlier.
4. When I am concerned about whether my values have changed over time.
9. When I am concerned about whether my beliefs have changed over time.
10. When I want to understand how I have changed from who I was before.

Social-Bonding Function Subscale

12. When I hope to also find out what another person is like.
13. When I want to develop more intimacy in a relationship.
16. When I want to develop a closer relationship with someone.
18. When I want to maintain a friendship by sharing memories with friends.
19. When I hope to also learn more about another person's life.

Directing-Behavior Function Subscale

21. When I want to remember something that someone else said or did that might help me now.
24. When I believe that thinking about the past can help guide my future.
25. When I want to try to learn from my past mistakes.
26. When I need to make a life choice and I am uncertain which path to take.
27. When I want to remember a lesson I learned in the past.

Note: The TALE opens with the instructions: "Sometimes people think back over their life or talk to other people about their life: It may be about things that happened quite a long time ago or more recently. We are not interested in your memory for a particular event, but more generally in how you bring together and connect the different events and periods of your life. Please select a response to answer these two questions: "In general, how often do you think back over your life?" and "In general, how often do you talk to others about what's happened in your life?" Next, we present a variety of situations. Please select *one* response on each scale to indicate how often, when you think back about or talk about your life, you do it for the reasons given. There are no right or wrong answers. Do not hesitate to use any of the points on the scale. If you never think back over your life for this reason, select 'Almost never.' Please answer every question." Items are in response to the stem statement, "I think back over or talk about my life or certain periods of my life…" The TALE features a five-point Likert-type scale (*1 = almost never; 2 = seldom; 3 = occasionally; 4 = often; 5 = very frequently*) (Bluck & Alea, 2011).

Table 6

MEIM–R Items

Commitment Subscale – Self
2. I have a strong sense of belonging to my own ethnic group.
3. I understand pretty well what my ethnic group membership means to me.
6. I feel a strong attachment toward my own ethnic group.
Exploration Subscale – Self
1. I have spent time trying to find out more about my ethnic group, such as its history, traditions, and customs.
4. I have often done things that will help me understand my ethnic background better.
5. I have often talked to other people in order to learn more about my ethnic group.

Note: Items are preceded by the open-ended question, “In terms of ethnic group, I consider myself to be (fill in the blank). Items will conclude with a list of the nine SONA-designated ethnicity/race groups[1], and the instruction to “select my ethnicity” from the list. Respondents are then asked, “In terms of ethnic group, what is your father’s ethnicity? What is your mother’s ethnicity?” and asked to respond in terms of the SONA-designated groups. The MEIM-R features a five-point Likert-type scale (*1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree*) (Phinney, 1992; Phinney & Ong, 2007).

Table 7

Results of Univariate (UV) and Multivariate (MV) Normality Diagnostics per Model

	Skewness		Kurtosis			
Model (n)	UV Mean Skew	MV Skewness *Z*-Score	UV Mean Kurtosis	Mardia's Relative (MV)	MV Kurtosis *Z*-Score	MV Skew and Kurtosis χ^2
EFA (921§)	−0.66	104.99**	−2.14*	1.52	51.02**	13626.01**
CFA (920§)	−0.67	104.61**	−1.84	1.52	50.83**	13527.11**
MCGFA						
Test-Retest						
Test (192)	−0.32	62.67**	−0.51	1.36	20.81**	4360.43**
Retest (192)	−0.16	64.16**	−0.32	1.39	21.34**	4571.85**
Gender						
Male (529)	−0.38	103.07**	−1.45	1.44	38.90**	12135.84**
Female (529§)	−0.51	83.90**	−1.35	1.44	36.79**	8397.96**
Ethnicity						
Caucasian (451§)	−0.42	78.12**	−0.94	1.41	33.18**	7203.43**
AA/Black (451)	−0.64	77.85**	−1.99*	1.44	33.92**	7210.32**
MTMM						
CRS-A (1841)	−0.95	120.92**	−2.49*	1.56	73.79**	20065.89**
TALE (1841)	−1.32	40.70**	−3.76**	1.31	36.37**	2979.05**

Note: All *n* denoted with § were randomly selected from total group sample to establish equal samples across MGCFA comparison group. All diagnostics were run in LISREL 9.1 (Scientific Software International, 2012). UV skew for all models was negative, as was kurtosis, indicating platykurtotic response data. Absolute value of UV average skew was for all models < 1.5, supporting the use of ULS estimation (Forero et al., 2009). Multivariate (MV) diagnostics were run treating data as continuous to obtain MV results including Mardia's Relative MV Kurtosis Index. Per Mardia's Index, absolute values < 1.96 indicate a nonsignificant difference from 0 (Mardia, 1970). MV normality diagnostics recommend that all models use the Satorra-Bentler χ^2 (*C3*) test-statistic, which corrects for MV normality. *Z*-significance tests are all two-tailed except for χ^2, the distribution for which is one-tailed (positive), with *p < .05 and **p < .001.

Table 8

Seven-Function Solution of CRS-A (41 Items) with Descriptive Statistics for Factors per EPAF

Factor and items (CRS function)	*Loading*	*Mean (SD)*
Factor 1: Social: Conversation		**4.78 (1.02)**
Give us something to talk about (CON)	.64	
Entertain myself with stories of past experiences (CON)	.79	
Entertain others with stories of past experiences (CON)	.87	
Share my life experiences with others (CON)	.71	
Have fun (CON)	.69	
Bond with others (RM)	.70	
Factor 2: Social: Perspective-Taking		**4.53 (1.30)**
Help me understand others (RM)	−.67	
Understand how others feel about an event (RM)	−.62	
Factor 3: Social: Relationship Maintenance		**4.37 (1.22)**
Remind myself or another that I am/he or she is loved (RM)	−.65	
Help myself feel close to family members (RM)	−.84	
Help myself understand family members better (RM)	−.85	
Help myself remember friends or family members (RM)	−.73	
Repair relations between myself and friends or family members (RM)	−.81	
Help resolve disputes between myself and friends or family (RM)	−.75	
Help myself understand friends better (RM)	−.73	
Help myself feel close to friends (RM)	−.68	
Factor 4: Directive: Behavioral Control, Teaching/Problem Solving		**4.51 (1.12)**
Emphasize the consequences of negative behavior (BC)	.78	
Clarify moral lessons (BC)	.82	
Bring to mind appropriate or preferred behavior (BC)	.84	
Explain ongoing activities (TPS)	.63	
Prepare myself or others for an upcoming event (TPS)	.63	
Help myself or others problem-solve (TPS)	.78	
So that I or another avoids repeating a past mistake at some later date (TPS)	.79	
To see how my or another's strengths can help solve a present problem (TPS)	.80	
Help lessen my or another's negative emotions (ER)	.71	
Factor 5: Directive: Emotion Regulation		**4.60 (1.18)**
Emphasize or clarify appropriate emotional responses (ER)	−.77	
Help me or another control emotions (ER)	−.82	
Help me or another cope with stressful or upsetting situations (ER)	−.86	
Help me make sense of my or another's emotions (ER)	−.88	
Help me or another process an emotional experience (ER)	−.89	
Help me or another understand how to feel (ER)	−.82	
Remind myself of how far I've come and all the experiences I've had (CS)	−.54	
Factor 6: Self		**4.30 (1.24)**
Help me feel good about myself (SELF)	−.78	
Build or maintain my sense of self (SELF)	−.89	
Build a unique individual identity for myself (SELF)	−.87	
Help me to feel or recognize that I am part of a larger group (SELF)	−.66	
Remind myself of what I was like when I was younger (SELF)	−.60	

Factor 7: Cognitive Skills		**4.31 (1.31)**
See how far back I can remember (CS)	−.82	
Test my memory (CS)	−.94	
Keep my memory and recall sharp (CS)	−.87	
Improve my ability to convey my past experiences and memories to others (CS)	−.68	

Note: Loadings per forced 7-function PAF solution using Quartermax rotation ($\delta = 0$) and based on a heterochoric correlation matrix. PAF run in R-Factor (Basto & Pereira, 2012). The function to which the item belonged in the Kulkofsky and Koh (2009) model is included in parentheses behind each item. CON = Conversation; PT = Perspective-Taking; RM = Relationship Maintenance; BC = Behavioral Control; TPS = Teaching/Problem-Solving; ER = Emotion Regulation; SELF = Self; and COG = Cognitive Skills. Negative factor loadings imply that respondents engage in corresponding joint reminiscence functions less often when high on the factor "trait."

Table 9

CRS-A Post-Factor Analysis Items with Their Matching Functions (CFA Validated)

Social Functions

Conversation

1. Give us something to talk about (Conversation)
2. Entertain myself with stories of past experiences (Conversation)
3. Entertain others with stories of past experiences (Conversation)
4. Share my experiences with others (Conversation)
5. Have fun (Conversation)
6. Bond with others (Relationship Maintenance)

Perspective Taking

7. Help me understand others (Relationship Maintenance)
8. Understand how others feel about an event (Relationship Maintenance)

Relationship Maintenance

9. Remind myself or another that I am/he or she is loved (Relationship Maintenance)
10. Help myself feel close to family members (Relationship Maintenance)
11. Help myself understand family members better (Relationship Maintenance)
12. Help myself remember friends or family members (Relationship Maintenance)
13. Repair relations between myself and friends or family members (Relationship Maintenance)
14. Help resolve disputes between myself and friends or family (Relationship Maintenance)
15. Help myself understand friends better (Relationship Maintenance)
16. Help myself feel close to friends (Relationship Maintenance)

Directive Functions:

Behavioral Control, Teaching, and Problem Solving

17. Emphasize the consequences of negative behavior (Behavioral Control)
18. Clarify moral lessons (Behavioral Control)
19. Bring to mind appropriate or preferred behavior (Behavioral Control)
20. Explain ongoing activities (Teaching/Problem Solving)
21. Prepare myself or others for an upcoming event (Teaching/Problem Solving)
22. Help myself or others problem-solve (Teaching/Problem Solving)
23. So that I or another avoids repeating a past mistake at some later date (Teaching/Problem Solving)
24. To see how my or another’s strengths can help solve a present problem (Teaching/Problem Solving)
25. Help lessen my or another’s negative emotions (Emotion Regulation)

Emotion Regulation

26. Emphasize or clarify appropriate emotional responses (Emotion Regulation)
27. Help me or another control emotions (Emotion Regulation)
28. Help me or another cope with stressful or upsetting situations (Emotion Regulation)
29. Help me make sense of my or another’s emotions (Emotion Regulation)
30. Help me or another process an emotional experience (Emotion Regulation)
31. Help me or another to understand how others feel (Emotion Regulation)

Self Function

32. Help me feel good about myself (Self)
33. Build or maintain my sense of self (Self)
34. Build a unique individual identity for myself (Self)
35. Help me to feel or recognize that I am part of a larger group (Self)
36. Remind myself of what I was like when I was younger (Self)

Note: This table reflects items and their factors per the exploratory factor analysis conducted in R-Factor (Basto & Pereira, 2012), and validated with confirmatory factor analysis in LISREL 9.1 (Scientific Software International, 2012). The final CRS-A was derived using principal axis factoring with quartermin oblique rotation on two-step heterochoric correlations.

Table 10

Six-Function Solution of CRS-A (36 Items) with Descriptive Statistics for Factors per EPAF

Factor and items (CRS function)	*Loading*	*Mean (SD)*
Factor 1: Social: Conversation		**4.78 (1.02)**
Give us something to talk about (CON)	.64	
Entertain myself with stories of past experiences (CON)	.79	
Entertain others with stories of past experiences (CON)	.88	
Share my life experiences with others (CON)	.68	
Have fun (CON)	.69	
Bond with others (RM)	.68	
Factor 2: Social: Perspective-Taking		**4.53 (1.30)**
Help me understand others (RM)	−.83	
Understand how others feel about an event (RM)	−.76	
Factor 3: Social: Relationship Maintenance		**4.36 (1.22)**
Remind myself or another that I am/he or she is loved (RM)	−.65	
Help myself feel close to family members (RM)	−.84	
Help myself understand family members better (RM)	−.85	
Help myself remember friends or family members (RM)	−.73	
Repair relations between myself and friends or family members (RM)	−.82	
Help resolve disputes between myself and friends or family (RM)	−.76	
Help myself understand friends better (RM)	−.74	
Help myself feel close to friends (RM)	−.68	
Factor 4: Directive: Behavioral Control, Teaching/Problem Solving		**4.51 (1.12)**
Emphasize the consequences of negative behavior (BC)	.78	
Clarify moral lessons (BC)	.82	
Bring to mind appropriate or preferred behavior (BC)	.84	
Explain ongoing activities (TPS)	.63	
Prepare myself or others for an upcoming event (TPS)	.63	
Help myself or others problem-solve (TPS)	.78	
So that I or another avoids repeating a past mistake at some later date (TPS)	.78	
To see how my or another's strengths can help solve a present problem (TPS)	.80	
Help lessen my or another's negative emotions (ER)	.71	
Factor 5: Directive: Emotion Regulation		**4.51 (1.23)**
Emphasize or clarify appropriate emotional responses (ER)	−.77	
Help me or another control emotions (ER)	−.83	
Help me or another cope with stressful or upsetting situations (ER)	−.86	
Help me make sense of my or another's emotions (ER)	−.87	
Help me or another process an emotional experience (ER)	−.88	
Help me or another understand how to feel (ER)	−.82	
Factor 6: Self		**4.30 (1.24)**
Help me feel good about myself (SELF)	−.78	
Build or maintain my sense of self (SELF)	−.88	
Build a unique individual identity for myself (SELF)	−.87	
Help me to feel or recognize that I am part of a larger group (SELF)	−.67	
Remind myself of what I was like when I was younger (SELF)	−.61	

Note: Loadings per forced 7-function PAF solution using Quartermax rotation ($\delta = 0$) and based on a heterochoric correlation matrix. PAF run in R-Factor (Basto & Pereira, 2012). The function to which the item belonged in the Kulkofsky and Koh (2009) model is included in parentheses behind each item. CON = Conversation; PT = Perspective-Taking; RM = Relationship Maintenance; BC = Behavioral Control; TPS = Teaching/Problem-Solving; ER = Emotion Regulation; SELF = Self; and COG = Cognitive Skills.

Table 11

Factor Correlations for 6-Function EPAF

	CONVO	PT	RM	BC/T/PS	ER	SELF
CONVO	1.00					
PT	.49	1.00				
RM	−.71	−.56	1.00			
BC/T/PS	−.63	−.52	.70	1.00		
ER	−.75	−.47	.66	.63	1.00	
SELF	−.60	−.58	.65	.49	.61	1.00

Note: Factor correlations for the six functions of CON = Conversation; PT = Perspective-Taking; RM = Relationship Maintenance; BC = Behavioral Control; TPS = Teaching/Problem-Solving; ER = Emotion Regulation; SELF = Self; All factor correlations significant at p < .05. Correlations are unattenuated values to be consistent with values reported in the phi matrix of the CFA (Miller, Jenkins, Kaplan, & Salonen, 1995, p. 1149).

Table 12

Six-Function Solution of CRS-A (36 Items) Including Descriptive Statistics for Factors per CFA

Factor and items (CRS function)	*Loading*	*Mean (SD)*
Factor 1: Social: Conversation		**4.86 (1.03)**
Give us something to talk about (CON)	.69	
Entertain myself with stories of past experiences (CON)	.76	
Entertain others with stories of past experiences (CON)	.75	
Share my life experiences with others (CON)	.84	
Have fun (CON)	.73	
Bond with others (RM)	.86	
Factor 2: Social: Perspective-Taking		**4.59 (1.20)**
Help me understand others (RM)	.83	
Understand how others feel about an event (RM)	.86	
Factor 3: Social: Relationship Maintenance		**4.46 (1.18)**
Remind myself or another that I am/he or she is loved (RM)	.78	
Help myself feel close to family members (RM)	.77	
Help myself understand family members better (RM)	.80	
Help myself remember friends or family members (RM)	.79	
Repair relations between myself and friends or family members (RM)	.81	
Help resolve disputes between myself and friends or family (RM)	.80	
Help myself understand friends better (RM)	.87	
Help myself feel close to friends (RM)	.83	
Factor 4: Directive: Behavioral Control, Teaching/Problem Solving		**4.50 (1.12)**
Emphasize the consequences of negative behavior (BC)	.73	
Clarify moral lessons (BC)	.78	
Bring to mind appropriate or preferred behavior (BC)	.81	
Explain ongoing activities (TPS)	.80	
Prepare myself or others for an upcoming event (TPS)	.76	
Help myself or others problem-solve (TPS)	.82	
So that I or another avoids repeating a past mistake at some later date (TPS)	.76	
To see how my or another's strengths can help solve a present problem (TPS)	.83	
Help lessen my or another's negative emotions (ER)	.81	
Factor 5: Directive: Emotion Regulation		**4.47 (1.24)**
Emphasize or clarify appropriate emotional responses (ER)	.87	
Help me or another control emotions (ER)	.87	
Help me or another cope with stressful or upsetting situations (ER)	.83	
Help me make sense of my or another's emotions (ER)	.87	
Help me or another process an emotional experience (ER)	.87	
Help me or another understand how to feel (ER)	.89	
Factor 6: Self		**4.31 (1.19)**
Help me feel good about myself (SELF)	.83	
Build or maintain my sense of self (SELF)	.85	
Build a unique individual identity for myself (SELF)	.81	
Help me to feel or recognize that I am part of a larger group (SELF)	.77	
Remind myself of what I was like when I was younger (SELF)	.68	

Note: Loadings are standardized values (square root of R^2). Means are based on 7-point Likert-type rating scale. All loadings significant at $p < .05$.

Table 13

Factor Correlations for 6-Function CFA

	CONVO	PT	RM	BC/T/PS	ER	SELF
CONVO	1.00					
PT	.63	1.00				
RM	.63	.78	1.00			
BC/T/PS	.56	.72	.77	1.00		
ER	.52	.70	.72	.83	1.00	
SELF	.56	.62	.76	.72	.73	1.00

Note: Factor correlations for the six functions of CON = Conversation; PT = Perspective-Taking; RM = Relationship Maintenance; BC = Behavioral Control; TPS = Teaching/Problem-Solving; ER = Emotion Regulation; SELF = Self; All factor correlations significant at $p < .05$. Correlations are unattenuated as reported in the phi matrix of CFA (Miller et al., 1995, p. 1149).

Table 14

Fit Indices for Test-Retest Invariance Tests of CRS-A 6-Function Model

Model	χ^2	*df*	χ^2/df	*CN*	*RMSEA*	*Δ RMSEA*	*NNFI*	*ΔNNFI*	*CFI*	*ΔCFI*	$\bar{T}_d$
2b. Configural											
	2247.97	1158	1.94	29.53	.050	--	.975	--	.977	--	--
2c. Metric											
	2288.83	1188	1.93	29.53	.049	−.001	.975	.000	.977	.000	< .0001
2d. Scalar											
	2031.62	1218	1.67	14.69	.042	−.007	.979	.004	.980	.003	99.38*
2e. Error variance											
	2034.29	1254	1.62	14.69	.040	−.002	.981	.003	.981	.001	< .0001
2f. Factor variance											
	2039.60	1260	1.62	14.69	.040	.000	.981	.000	.981	.000	< .0001
2g. Factor covariance											
	2039.43	1275	1.60	14.69	.040	.000	.981	.000	.981	.000	< .0001
2h. Factor means											
	2237.82	1281	1.75	29.53	.044	.004	.980	−.001	.980	−.001	13.95

Note: Both the Tests and Retest groups = 192. The per-model MGCFA n = 384. Reported chi-square test statistics are Satorra-Bentler (*C3*), which correct for multivariate nonnormality. *RMSEA*, *NNFI*, and *CFI* were derived using the corresponding *C3* model chi-squares. $\bar{T}_d$ is the standard maximum likelihood chi-square difference between the normally distributed maximum likelihood chi-square (*C2*) and the corrected Satorra-Bentler chi-square (*C3*). It is necessary to conduct model change significance tests with the corrected $\bar{T}_d$ because the SB chi-square does not follow a chi-square distribution. Therefore, the standard chi-square difference test, whereby each subsequent model chi-square is compared to the previous, is inappropriate (Satorra, 2000; Satorra & Bentler, 1999). Invariance was rejected at the .01 significance level (Raykov & Marcoulides, 2006, p. 215), where *p < .001.

Table 15

Fit Indices for Gender Invariance Tests of CRS-A 6-Function Model

Model	χ^2	*df*	χ^2/df	*CN*	*RMSEA*	*Δ RMSEA*	*NNFI*	*ΔNNFI*	*CFI*	*ΔCFI*	$\overline{T}_d$
1. Configural											
	3182.56	1158	2.75	15.87	.041	--	.987	--	.988	--	--
2. Metric											
	3241.63	1188	2.73	15.87	.040	−.001	.987	.000	.987	.000	< .001
3. Scalar											
	3379.61	1218	2.77	12.01	.041	.001	.985	−.002	.985	−.002	76.27*
4. Error variance											
	3359.36	1254	2.68	12.01	.040	−.001	.986	.001	.986	.001	< .001
5. Factor variance											
	3366.91	1260	2.67	12.01	.040	.000	.986	.000	.986	.000	< .001
6. Factor covariance											
	3371.27	1275	2.64	12.01	.039	−.001	.986	.000	.986	.000	< .001
7. Factor means											
	3118.57	1281	2.43	15.87	.037	−.003	.989	.003	.989	.003	10.82

Note: The actual male sample = 529. To maintain equal groups, 529 female cases were randomly selected from total 1305. The per-model MGCFA n = 1058. Reported chi-square test statistics are Satorra-Bentler (*C3*), which correct for multivariate nonnormality. *RMSEA*, *NNFI*, and *CFI* were derived using the corresponding *C3* model chi-squares. $\overline{T}_d$ is the standard maximum likelihood chi-square difference between the normally distributed maximum likelihood chi-square (*C2*) and the corrected Satorra-Bentler chi-square (*C3*). It is necessary to conduct model change significance tests with the corrected $\overline{T}_d$ because the SB chi-square does not follow a chi-square distribution. Therefore, the standard chi-square difference test, whereby each subsequent model chi-square is compared to the previous, is inappropriate (Satorra, 2000; Satorra & Bentler, 1999). Invariance was rejected at the .01 significance level (Raykov & Marcoulides, 2006, p. 215), where *$p < .001$.

Table 16

Fit Indices for Ethnic (Caucasian and African-American/Black) Invariance Tests of CRS-A 6-Function Model

Model	χ^2	*df*	χ^2/df	*CN*	*RMSEA*	*Δ RMSEA*	*NNFI*	*ΔNNFI*	*CFI*	*ΔCFI*	$\bar{T}_d$
4b. Configural											
	3259.91	1158	2.82	14.91	.045	--	.981	--	.983	--	--
4c. Metric											
	3318.08	1188	2.79	14.91	.045	.000	.982	.001	.983	.000	< .001
4d. Scalar											
	3333.47	1218	2.74	10.90	.044	−.001	.980	−.002	.981	−.002	90.38*
4e. Error variance											
	3321.54	1254	2.65	10.90	.043	−.001	.981	.001	.981	.000	< .001
4f. Factor variance											
	3328.73	1260	2.64	10.90	.043	.000	.981	.000	.981	.000	< .001
4g. Factor covariance											
	3333.02	1275	2.61	10.90	.042	−.001	.981	.000	.981	.000	< .001
4h. Factor means											
	3193.56	1281	2.49	14.90	.041	−.001	.985	.004	.984	.003	12.84

Note: The actual African-American/Black sample = 451. To maintain equal groups, 451 Caucasian cases were randomly selected from total 771. Reported chi-square test statistics are Satorra-Bentler (*C3*), which correct for multivariate nonnormality. *RMSEA*, *NNFI*, and *CFI* were derived using the corresponding *C3* model chi-squares. $\bar{T}_d$ is the standard maximum likelihood chi-square difference between the normally distributed maximum likelihood chi-square (*C2*) and the corrected Satorra-Bentler chi-square (*C3*). It is necessary to conduct model change significance tests with the corrected $\bar{T}_d$ because the SB chi-square does not follow a chi-square distribution. Therefore, the standard chi-square difference test, whereby each subsequent model chi-square is compared to the previous, is inappropriate (Satorra, 2000; Satorra & Bentler, 1999). Invariance is rejected at the .01 significance level (Raykov & Marcoulides, 2006, p. 215), where $*p < .001$.

Table 17

Correlations Between TALE Functions and Validated CRS Functions

Items	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*
TALE items										
1. Directive	–	.64***	.61***	.24**	.26***	.22**	.32***	.20**	.18**	.25***
2. Self		–	.56***	.23***	.18**	.29***	.34***	.22**	.19**	.33***
3. Bonding (Social)			–	.15*	.08	.18**	.28***	.19**	.16*	.14*
CRS items										
4. Emotion Regulation				–	.77***	.69***	.54***	.21**	.26***	.63***
5. Directive					–	.55***	.58***	.33***	.45***	.53***
6. Positive Emotionality						–	.64***	.46***	.44***	.53***
7. Self in Relation to Others							–	.58***	.61***	.50***
8. Conversation								–	.56***	.22**
9. Cognitive Skills									–	.25***
10. Peer Relationships										–

Note: ***p < .001, **p < .01, *p < .05. Kulkofsky & Koh (2009).

Table 18

Correlations (Percent of Unique Variance Accounted for) Between TALE Functions and the Six CRS-A Functions

TALE / **CRS-A**	Social	Directive	Self
Conversation	.42*** (6.0%)	.37*** (2.5%)	.27 (< 0.3%)
Perspective-Taking	.48*** (8.9%)	.40*** (2.0%)	.30** (< 0.3%)
Relationship Maintenance	.50*** (7.2*)	.46*** (3.1%)	.38*** (1.3%)
Behavioral Control/Teaching/Problem Solving	.46*** (2.2%)	.57*** (10.8%)	.41*** (1.5%)
Emotion Regulation	.28*** (5.4%)	.52*** (6.0%)	.44*** (2.2%)
Self	.23*** (3.6%)	.457*** (3.3%)	.20*** (4%)

Note: ***$p < .001$, **$p < .01$, *$p < .05$.

Table 19

Goodness of Fit Indices for MTMM Models Using 6-Function CRS-A and TALE

Model	*Condition*	χ^2	*df*	χ^2/df	*RMSEA*	*NNFI*	*CFI*
5b. CFA-CTCM	13.56	9762.41	1169	8.35	.063	.978	.980
5c. CFA-NTCM	13.56	16622.60	1224	13.58	.082	.962	.963
5d. CFA-PCTCM	13.56	12746.86	1172	10.88	.073	.970	.963
5e. CFA-CTUM	13.56	10020.01	1170	8.56	.064	.977	.979

Note: N = 1841 for each the CRS-A and TALE (Bluck & Alea, 2010). Reported chi-square test statistics are Satorra-Bentler (*C3*), which corrects for multivariate nonnormality. *RMSEA*, *NNFI*, and *CFI* are derived from the *C3* chi-square. MTMM paradigm per Byrne (2013), whereby *CTCM* = Correlated Traits/Correlated Methods; *NTCM* = No Traits/Correlated Methods; *PCTCM* = Perfectly Correlated Traits/Correlated Methods; and *CTUM* = Correlated Traits/Uncorrelated Methods. Additionally, Condition = Condition number, where values > 15 indicate potential issues with multicollinearity.

Table 20

Goodness of Fit Indices for MTMM Nested Model Comparisons

Model comparison	$\overline{T}_d$	*Δdf*	*ΔCFI*	*p-value*
Test of Convergent Validity				
CTCM vs. NTCM	226.00	30	−.017	< .001
Test of Discriminant Validity (Traits)				
CTCM vs. PCTCM	627.54	82	−.017	< .001
Test of Discriminant Validity (Methods)				
CTCM vs CTUM	279.27	36	−.019	< .001

Note: N = 1841 for each the CRS-A and TALE (Bluck & Alea, 2010). Change in chi-square test statistics are Satorra-Bentler (*C3*) chi-squares, which are corrected for multivariate nonnormality. Change in *RMSEA*, *NNFI*, and *CFI* are also based on fit indices derived from the *C3* chi-square. MTMM comparison paradigm per Byrne (2013), whereby *CTCM* = Correlated Traits/Correlated Methods; *NTCM* = No Traits/Correlated Methods; PCTCM = Perfectly Correlated Traits/Correlated Methods; and *CTUM* = Correlated Traits/Uncorrelated Methods. Because *C3* chi-squares are not chi-square distributed, $\overline{T}_d$ reflects the adjusted value appropriate for model comparison (Satorra & Bentler, 2000). $|\Delta CFI| \geq .01$ indicates significant change. (Hu & Bentler, 1999). Results indicate that the CRS-A demonstrated convergent validity, trait discriminant validity, and evidence of method bias.

Table 21

Factor Correlations for 3-function CRS-A

		Social	**Directive**	**Self**
CRS-A	**Social**	1.00		
	Directive	.80	1.00	
	Self	.77	.75	1.00
TALE	**Social**	1.00		
	Directive	.91	1.00	
	Self	.75	.57	1.00

Note: All factor correlations significant at $p < .05$. Average correlation for the CRS-A = .77. Average correlation for the TALE = .74.

Table 22

Mean Scale Scores for 6-Function CRS-A

CRS-A Functions	Mean (SD)
Conversation	4.85 (1.02)
Perspective-Taking	4.54 (1.28)
Relationship Maintenance	4.40 (1.21)
Behavioral Control/Teaching/Problem Solving	4.54 (1.11)
Emotion Regulation	4.52 (1.24)
Self	4.32 (1.25)

Note: Scale scores were derived using the Caucasian (randomly selected, n = 451) and African-American/Black (n = 451) samples on which the CRS-A ethnic invariance tests were conducted. Because the samples were used to validate the CRS-A, results using the validation samples are strictly provisional, and meant to inform future research only.

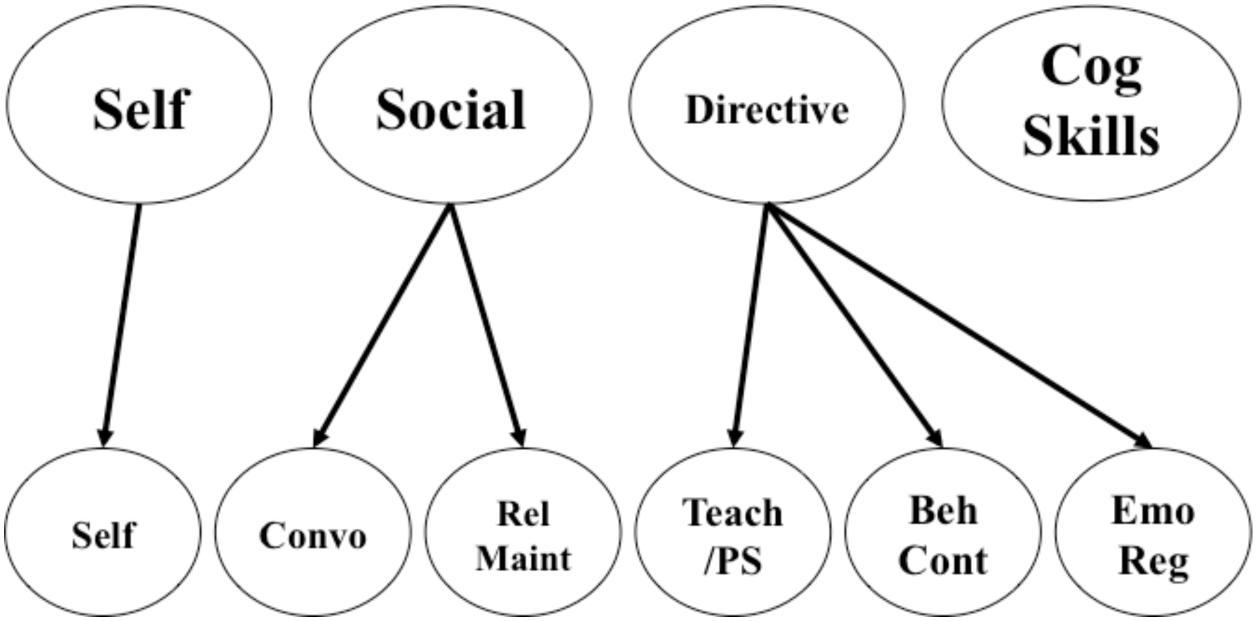

Figure 1. Conceptual model of the theoretical CRS (Kulkofsky & Koh, 2009) as it hypothetically maps onto the three theoretical functions of Social, Directive, and Self. Cognitive Skills is theorized to be distinct from the Social, Directive, and Self functions. The CRS Self function is hypothesized to map onto the TALE Self function. The CRS Conversation and Relationship Maintenance functions are thought to belong to the TALE Social function. The CRS Teaching/Problems Solving, Behavioral Control, and Emotion Regulation functions are thought to be subfunctions of the TALE Directive function.

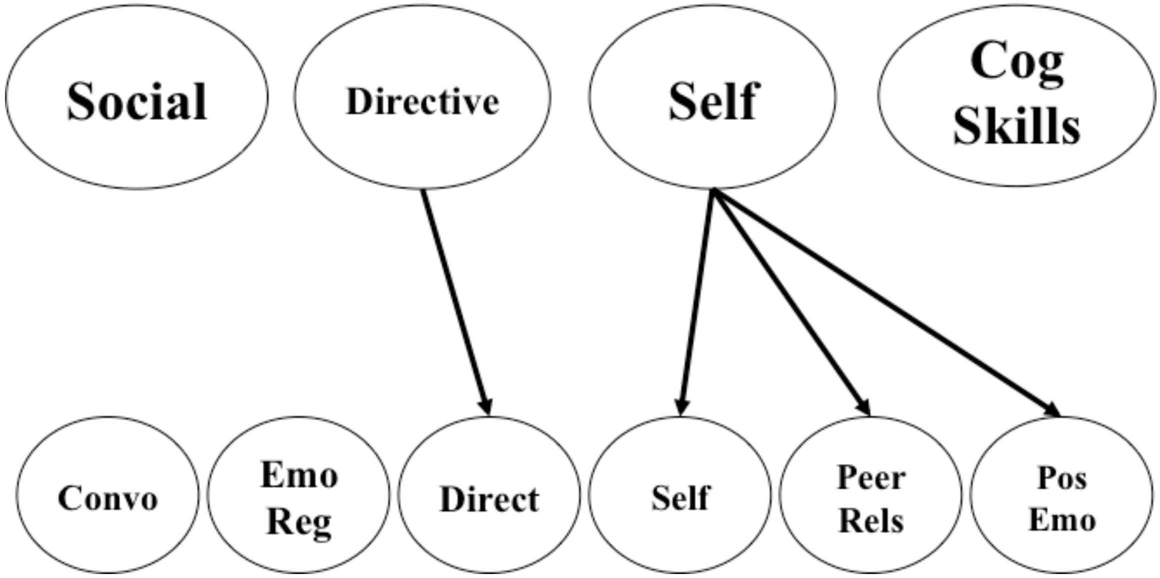

Figure 2. Conceptual model of the validated CRS (Kulkofsky & Koh, 2009) as it mapped onto the three theoretical functions of the TALE (Bluck et al., 2005; Bluck & Alea, 2011). Cognitive Skills emerged as a new function distinct from the Self, Directive, and Social functions. The CRS functions of Conversation and Emotion Regulation were not uniquely predicted by any TALE function. The TALE function of Directive uniquely predicted the CRS Directive function. The TALE Self function uniquely predicted the CRS Self, Peer Relationships, and Positive Emotionality functions.

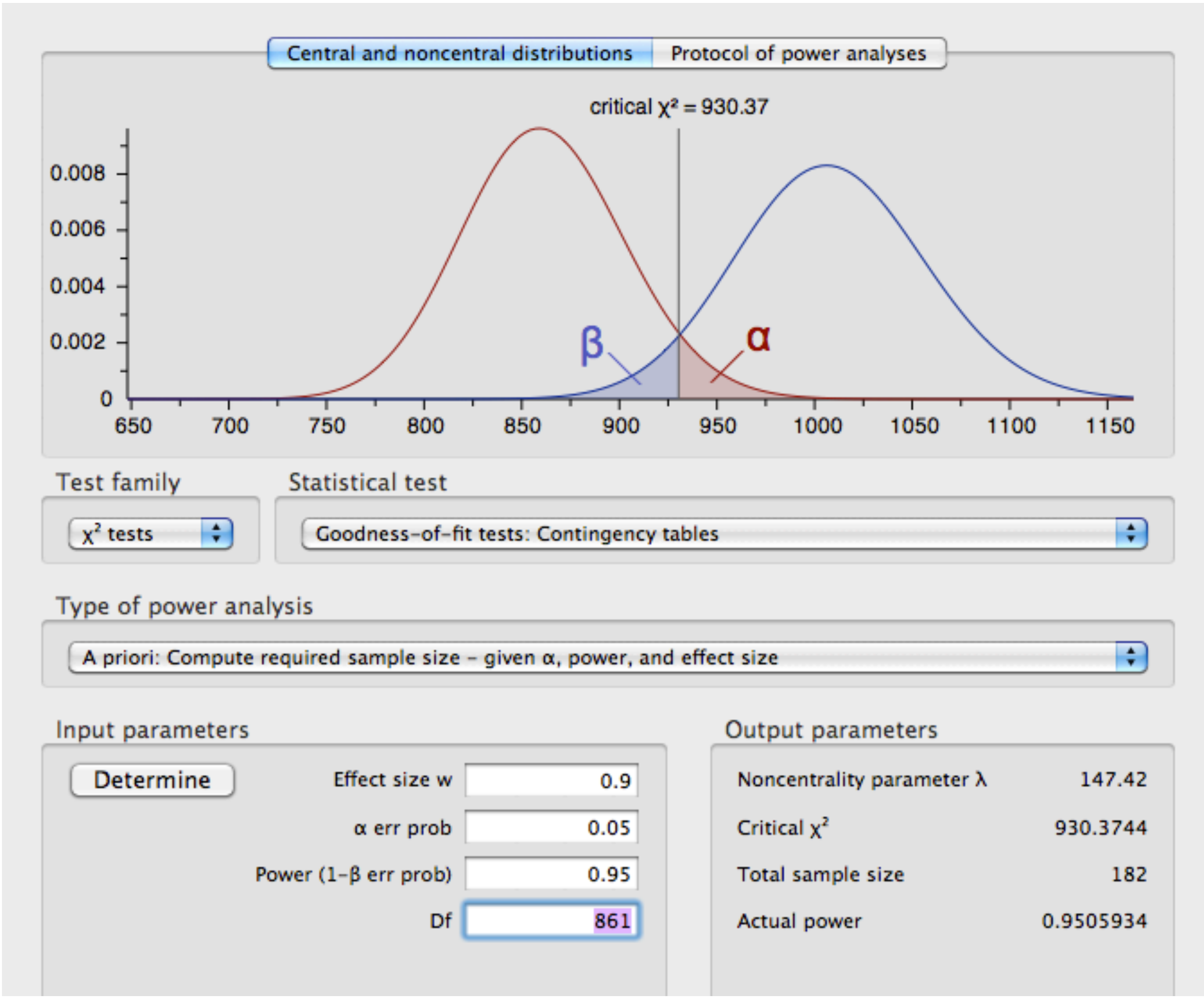

Figure 3. Prospective power analysis for the general utility EFA and the factorial validity CFA of CRS-A at α = .05 and $1-\beta$ = .95. *Df* = 861, Effect size = .90. Degrees of freedom were calculated using the formula p(p + 1)/2, where p (number of indicators) = 41. Effect size of .90 reflects the accepted lower limit of the close-fit estimations per the Comparative Fit Index (*CFI*) and the Non-Normed Fit Index (*NNFI*) per MacCallum, Browne, & Sugawara (1996). No model parameters on which to base a prospective power analysis of the original CRS (Kulkofsky & Koh, 2009) was provided by the study authors.

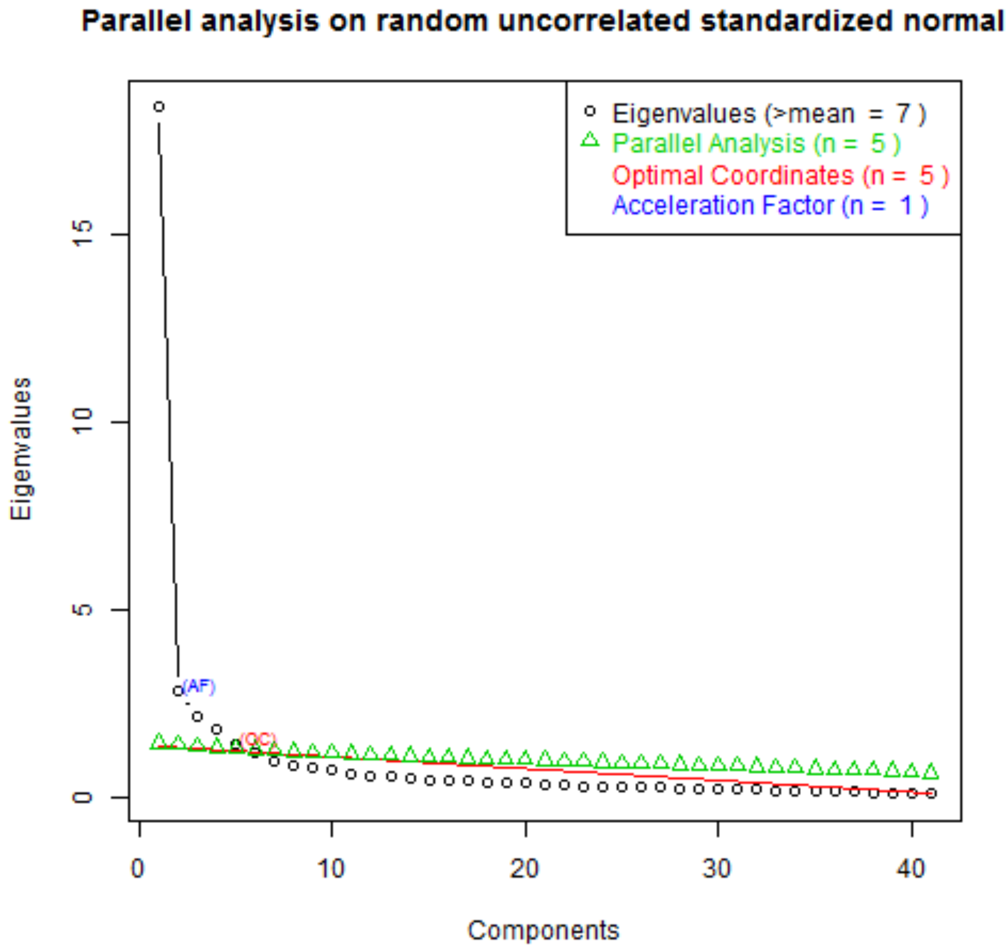

Figure 4. Parallel analysis (PA) on data permutation (for ordinal variables) plot depicting the mean eigenvalue and PA extraction diagnostic results. A recommended version of the optimal coordinate (OC) and acceleration factor (AF) for ordinal data has not been established (Courtney, 2013, p. 5), so those results are disregarded The intersection of lines, at which the optimal number of factors (components) to retain occur, recommends five to seven factors. Given that the Kaiser method (mean eigenvalue) is known to overextract (Basto & Pereira, 2012), the true number of factors is likely five (per PA) or six.

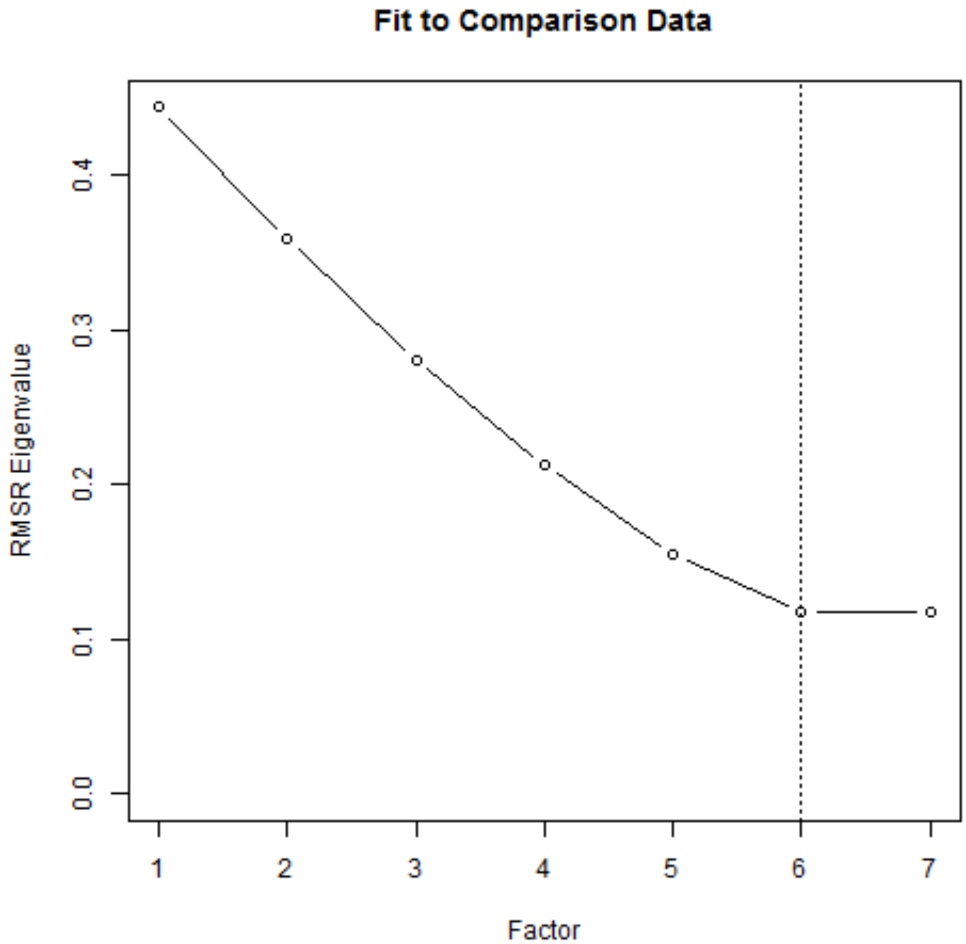

Figure 5. The fit of comparison data (CD) plot, which is based on difference between the observed data and a worst-case model, indicates that the optimal number of factors to retain is six. The plot supports the CD diagnostic results, which also recommended six factors.

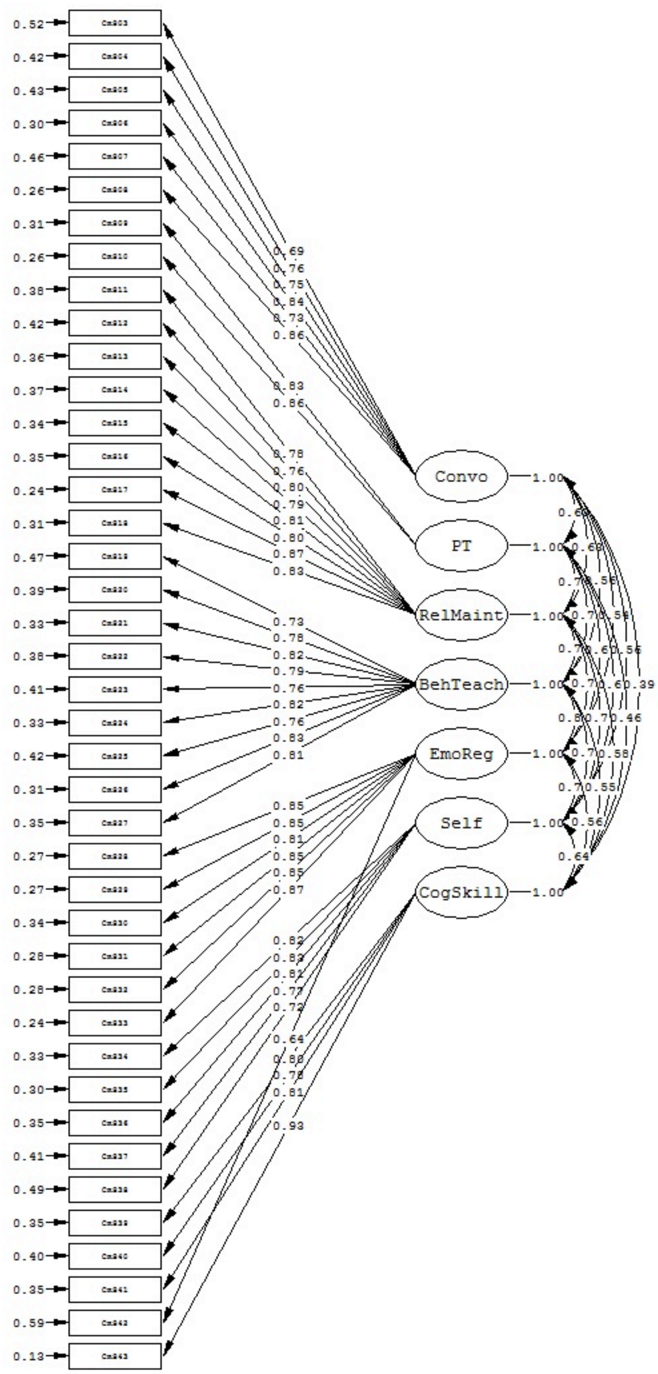

Figure 6. Path diagram of standardized factor loadings of the 7-function version of CRS-A model as detailed in Table 8. All loadings, $p < .05$.

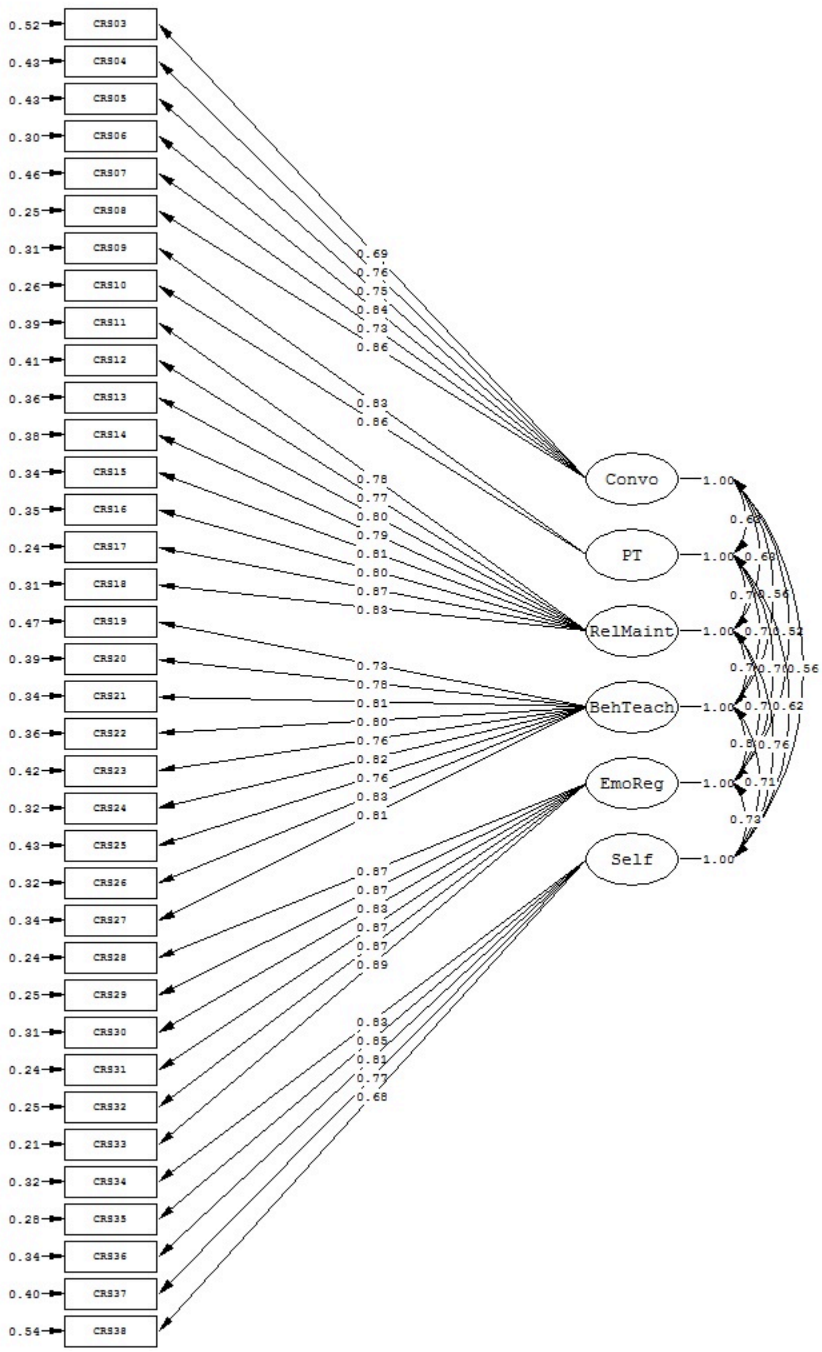

*Figure 7.*Path diagram of standardized factor loadings of the 6-function version of the CRS-A model and as detailed in Table 12. All loadings, $p < .05$.

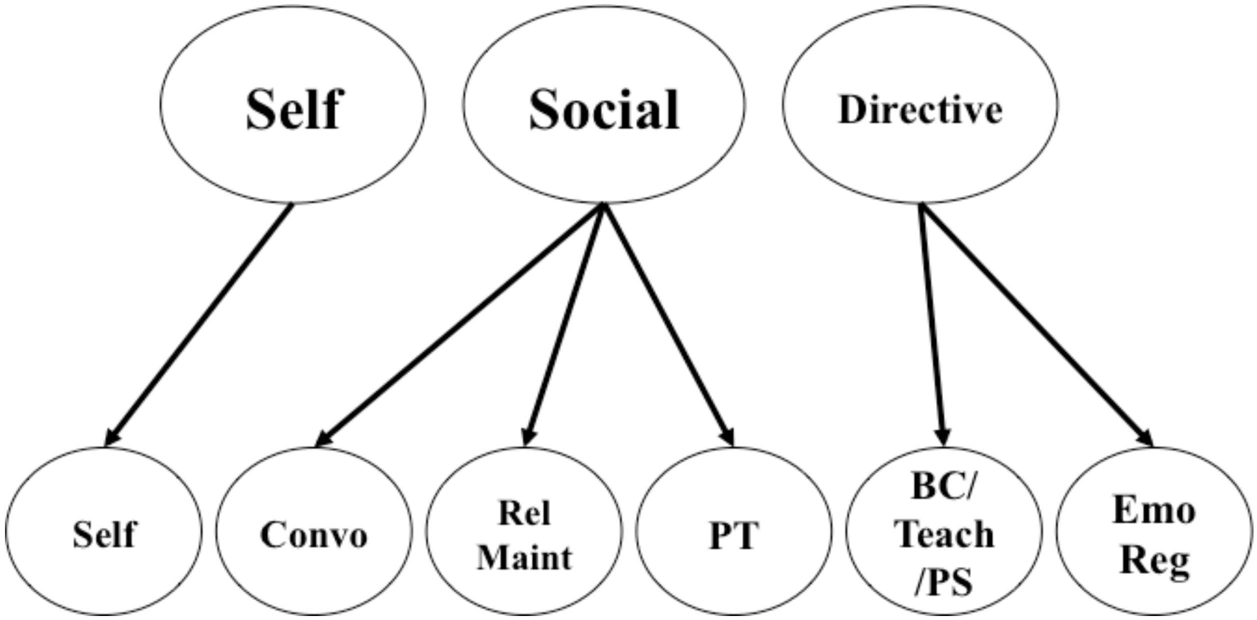

Figure 8. CRS-A conceptual model. Self, Social, and Directive are the three theoretical functions validated with the TALE (Bluck et al., 2005; Bluck & Alea, 2011). Self was also validated by the CRS-A, as were the subfunctions of Conversation, Relationship Maintenance, Perspective-Taking, Behavioral Control/Teaching/Problems-Solving, and Emotion Regulation. Perspective-Taking is novel to the CRS-A and implies a subfunction relevant to adult AM. Behavioral Control and Teaching/Problem-Solving, which were two subfunctions in the Kulkofsky and Koh (2009) model , fused during CRS-A validation to imply that, for adults, they comprise a single function.

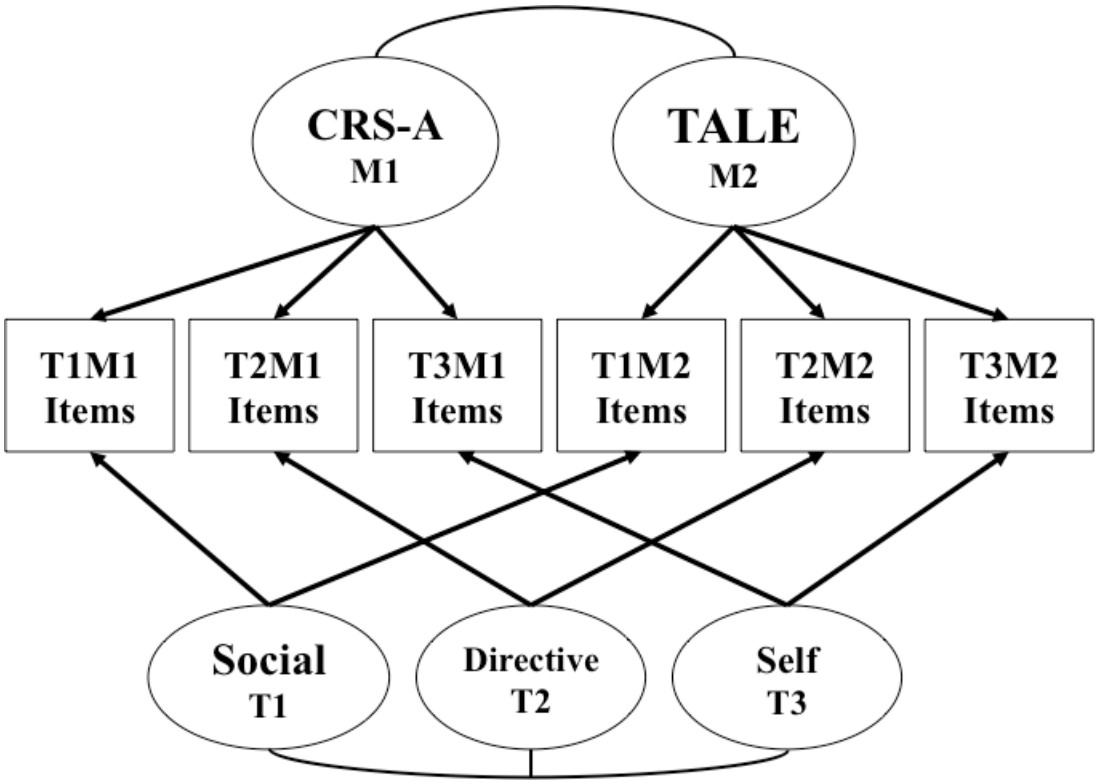

Figure 9. Correlated Traits Correlated Methods (CTCM) MTMM CFA conceptual model per Byrne (2013).

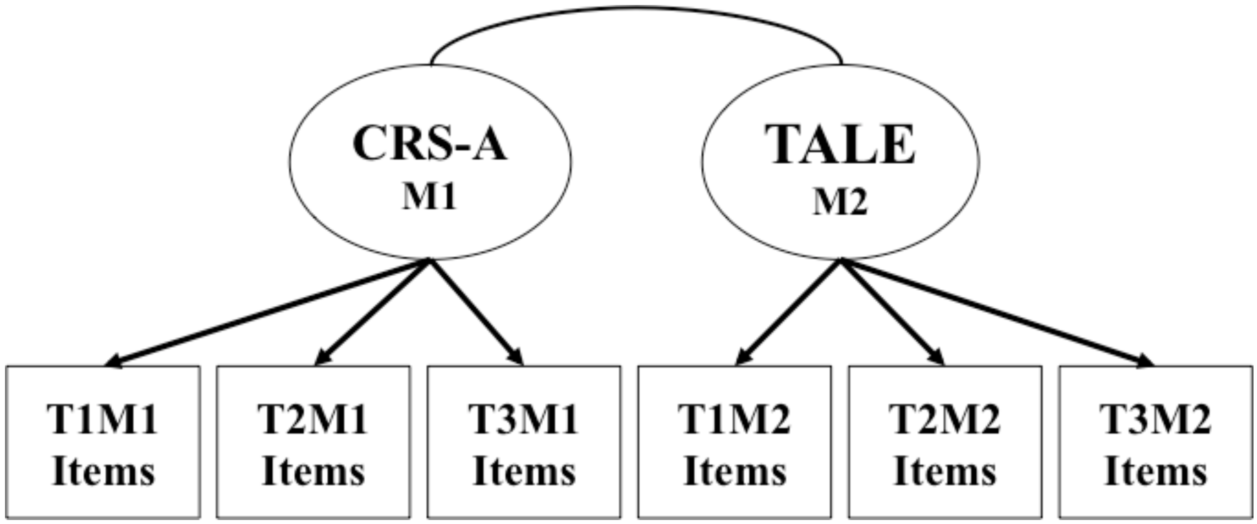

Figure 10. No Traits Correlated Methods (NTCM) MTMM CFA conceptual model per Byrne (2013).

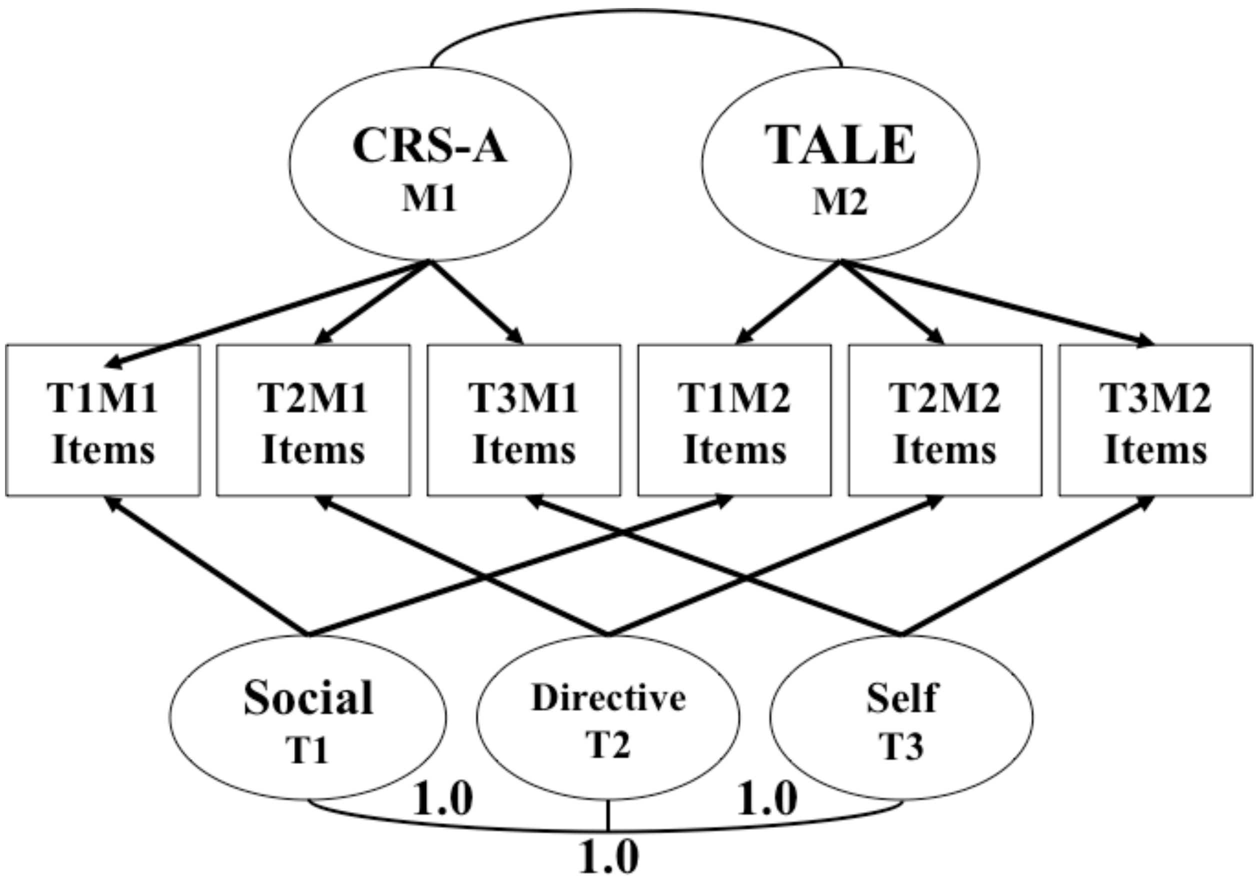

Figure 11. Perfectly Correlated Traits Correlated Methods (PCTCM) MTMM CFA conceptual model per Byrne (2013).

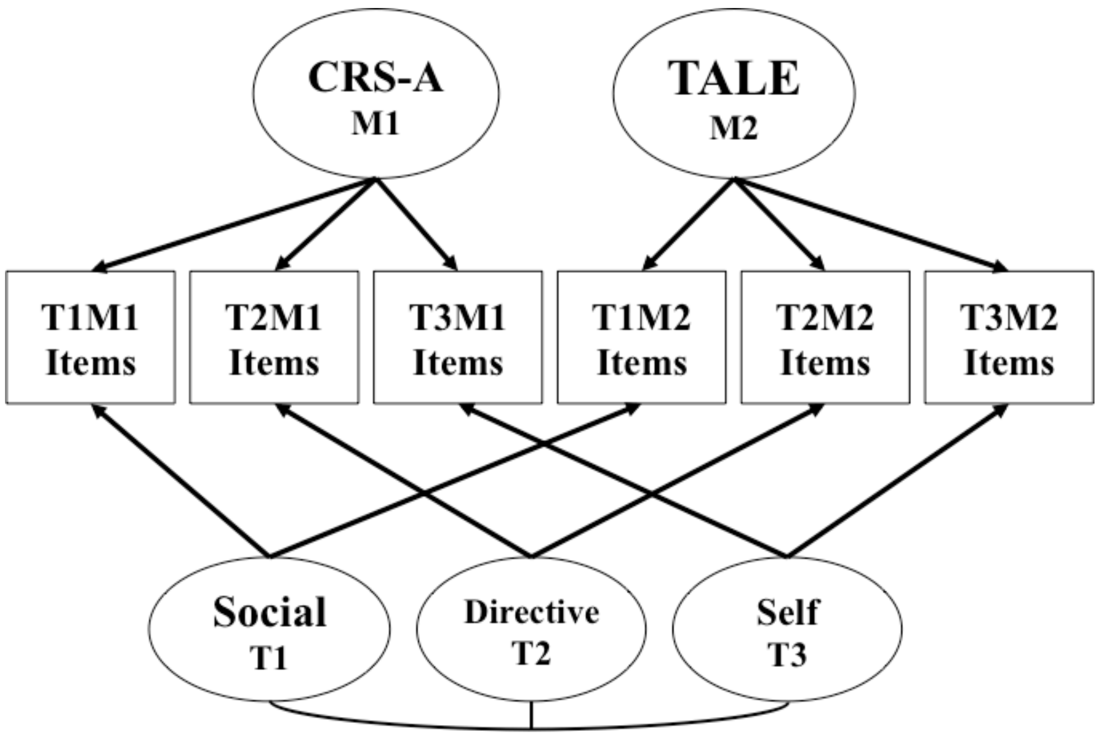

Figure 12. Correlated Traits Uncorrelated Methods (CTUM) MTMM CFA conceptual model per Byrne (2013).

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ABSTRACT

EVERYDAY MEMORY: AN EXPANDED VIEW OF AUTOBIOGRAPHICAL MEMORY FUNCTIONS

by

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The current study investigated an expanded set of everyday autobiographical memory (AM) functions as proposed by developers of the 7-function Child-Caregiver Reminiscence Scale (CRS) (Kulkofsky & Koh, 2009). The current study adapted the theoretical CRS for use with diverse, adult samples. Participants (N = 1841) from a large, urban university completed the CRS-A online over the course or two academic semesters. Validation analyses included EFA using principal axis factoring, CFA, MGCFA invariance testing, and MTMM tests of construct validity (convergent and discriminant) and method effects. Results yielded evidence for a 6-function (Conversation, Perspective-Taking, Relationship Maintenance, Behavioral Control/Teaching/Problem-Solving, Emotion Regulation, and Self) model that demonstrated invariance across time, gender, and ethnicity/race. Provisional evidence showed that the Conversation and Behavioral Control/Teaching/Problem-Solving functions were used differentially across Caucasian and African-American/Black groups. Implications, limitations, and future directions are discussed.

AUTOBIOGRAPHICAL STATEMENT

A native of South Central Wisconsin, Jana Ranson graduated with high distinction from the University of Minnesota-Twin Cities with a Bachelor of Individualized Studies (Psychology, Philosophy of Science, History of Science). As a doctoral student in Wayne State University's Cognitive, Developmental, and Social Psychology program, her academic and professional interests are broadly in social/cognitive psychology research and statistical measure and analysis for the behavioral sciences, with an emphasis in the empirical validation of theory from the autobiographical memory functions and mental time travel (MTT) domains. Ms. Ranson is planning on completing her Ph.D. in 2016 from Wayne State University.