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The Development and Validation of Implicit Measures of Emotional Intelligence

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THE DEVELOPMENT AND VALIDATION OF IMPLICIT MEASURES OF EMOTIONAL INTELLIGENCE

A Masters Thesis

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In Partial Fulfillment

Of the Requirements for the Degree

Master of Science, Psychology

By

Ricardo Rashawn Brooks

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ABSTRACT

Emotional intelligence (EI) has attracted much attention in the decades since Goleman's (1995) claim that EI is important for success in a wide range of social and professional roles. With this interest has come much debate about whether EI should be defined and measured as a set of abilities or as a set of dispositional self-perceptions. The latter is typically assessed with self-report measures that are susceptible to contamination related to inaccurate self-knowledge and impression management artifacts – problems that may be mitigated by implicit measures. This research used Implicit Association Test (IAT) procedures to develop implicit measures of EI and investigated relationships with theoretically related explicit (self-report) measures with a sample of Amazon's Mechanical Turk workers. The results of confirmatory factor analyses of nested latent trait models provided some evidence of convergent and discriminant validity.

KEYWORDS: emotional intelligence, implicit measures, Implicit Association Test, construct validity, confirmatory factor analysis, nested latent trait models, Mechanical Turk

This abstract is approved as to form and content

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Donald L. Fischer, PhD
Chairperson, Advisory Committee
Missouri State University

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INTRODUCTION

Emotional Intelligence (EI) is a construct that has garnered interest from both researchers and practitioners (Lievens & Chan, 2010). Salovey and Mayer (1990) first introduced EI as a construct over 25 years ago. The theory was further popularized by social scientist Daniel Goleman (1995) after publishing his book, which claimed that the importance of EI could outweigh that of cognitive ability (IQ), regarding success in social and professional roles. Despite the construct's popularization, researchers have continued to struggle with whether EI is a legitimate construct and how to operationally define it (Antonakis, Ashkanasy, & Dasborough, 2009; Locke, 2005; Mayer, Salovey & Caruso, 2008; Petrides, 2011). This uncertainty regarding EI has led to vast differences in measurement approaches to emotional intelligence. This lack of clarity regarding operationalization and measurement of EI has led to continued criticism of the construct (Tett, Fox, & Wang, 2005; Mayer, Salovey, & Caruso, 2004).

Despite the debate over EI as a legitimate construct, scholars do recognize EI as a standard concept (Antonakis et al., 2009). In the workplace, practitioners continue to place value on selecting and training a more emotionally intelligent workforce (Fineman, 2004; Nafukho & Muyia, 2014). Organizations have even begun investing resources into training programs designed to increase EI of employees and leadership. In an attempt to establish the usefulness of EI in the workplace, the construct has been examined with leadership, job performance, emotional health, conflict management, and employee health (Harms & Credé, 2010; Joseph & Newman, 2010; Joseph, Jin, Newman, & O'Boyle, 2015; Martins, Ramalho, & Morin, 2010; O'Boyle, Humphrey, Pollack,

Hawver, & Story, 2011; Elias et al., 1997).

Literature Review

Ability Versus Trait Debate. Within the literature, EI is conceptualized as either an ability or trait-based construct. Those who conceptualize EI as an ability view it as the accumulation of behaviors and abilities that contribute to an individual's success at recognizing and managing the emotions of oneself and others. Mayer et al. (2008) have further defined EI as the ability to engage in sophisticated information processing about one's own and others' emotions and the ability to use this information as a guide to thinking and behavior (p. 503). In order to measure the elusive construct of Emotional Intelligence, the aforementioned researchers designed the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT V2.0). The MSCEIT defines EI using four skillsets: perceiving emotion accurately, using emotion to facilitate thought, understanding emotion, and managing emotion (Mayer, Caruso, Salovey & Sitarenios, 2003). The perceiving emotion accurately skillset describes the individual's aptitude at identifying the emotion in faces, pictures, and other non-verbal expressions. The using emotion to facilitate thought skillset describes the extent to which one can employ emotions to enhance thinking that will guide future effective behavior. The understanding emotion skillset is the ability to comprehend, examine, reflect, and recognize emotional information. Lastly, the managing emotion skillset is the ability to control emotions for personal and interpersonal growth and to achieve one's goals (Mayer et al, 2004; Mayer et al., 2003).

The trait based model views EI as dispositional, an individual difference amongst

people. This model characterizes EI as a "constellation of behavioral dispositions and self-perceptions concerning one's ability to recognize, process, and utilize emotion-laden information" (Petrides & Furnham, 2003 p. 278). Petrides and Furnham provide examples such as self-efficacy, empathy, and optimism. In order to measure their trait based model of EI Petrides and Furnham developed the Trait Emotional Intelligence Questionnaire (TEIQue). The TEIQue defines trait EI as a hierarchical construct involving four factors and 15 facets. The four factors are identified as emotionality (being emotionally capable), self-control (possessing willpower), sociability (being socially capable), and well-being (being overall well-adapted). In turn, emotionality is composed of four facets: trait empathy, emotion perception, emotion expression, and relationships. Self-control is composed of three facets: stress management, low impulsiveness, and emotion regulation. Sociability is composed of emotion management, assertiveness, and social awareness. The last factor, Well-being, is composed of self-esteem, trait happiness, and trait optimism.

Measuring Emotional Intelligence. Those that conceptualize EI as inherent traits tend to use self-report measures while those in the ability camp rely on maximum-performance tests (Petrides, 2011). Although researchers disagree on the nature of EI (ability vs. trait) and its measurement, researchers do agree on one notion. That is, that trait EI and ability EI measurements do not tap into the same constructs (Lievens & Chan, 2010). Van Rooy, Viswesvaran, and Pluta (2005) conducted a meta-analysis which showed that the different measures for EI were minimally correlated with one another, supporting the explicit distinction between them. Trait EI has been shown to correlate more so with personality measures while ability EI typically correlated with cognitive

ability measures (Petrides, 2011; Lievens & Chan, 2010).

Both measurement approaches have received criticism for their claims. Ability (i.e., maximum-performance) measures define emotional intelligence as a true intelligence. However, researchers criticize this claim as just another faux intelligence. Petrides (2011) highlights the difficulty of standardizing emotionally laden items or tasks. In order to define ability EI as a true intelligence it would require the use of an IQ-type procedure – involving objectively correct and incorrect responses. For example, The MSCEIT V2.0 relies on consensus or expert-scoring in order to create objective (i.e., right or wrong) responses. These procedures have been shown to yield scores that are foreign to cognitive ability as well as present issues of confounding (e.g., vocabulary size & stereotypical judgements).

Trait EI (also labeled as emotional self-efficacy) and the self-report measures that are used have garnered their fair share of criticism as well. Two focal critiques include: the presence of impression management artifacts and inflation of correlations due to common method variance (Lievens & Chan, 2010). Impression management or faking is especially problematic with variables such as EI (i.e., socially sensitive variables) in a setting where measurement outcomes influence employment opportunities. Aside from impression management, self-knowledge artifacts or inaccurate self-awareness can also plague self-report measures. That is, one’s own conscious self-awareness may not accurately reflect others’ relevant perceptions and experiences regarding them (Greenwald, McGhee & Schwartz, 1998). In response to this issue, Goleman (1995) advocates multi-source ratings to asses EI. Typically, these ratings are conducting using significant others of the target individual (peers, superiors, and subordinates).

As it stands, the two primary approaches to measuring trait EI appear to be insufficient. Therefore, one might look to develop and alternative method of measurement in order to bridge the gap between the self-report measures and the multi-source ratings. Both approaches can be categorized as explicit measurement approaches, as they provide opportunities for one to consciously reflect on their responses. As suggested by Zeidner, Matthews, and Roberts (2009), using an implicit measurement approach may better suit the construct of emotional intelligence. They argue that EI is comprised of unconscious (i.e., implicit) psychological processes and therefore needs a measurement tool designed for such processes. These implicit psychological processes according to Greenwald and Banaji (1995) can include cognitions, feelings and evaluations that are not necessarily available to conscious awareness, conscious control, conscious intention, or self-reflection. That is, the signature of implicit social cognitions is that "traces of past experiences affect some performance – even though the influential earlier experience is not remembered in the usual sense – that is, it is unavailable to self-report or introspection" (p. 4-5).

While explicit processes can be easily conveyed, implicit processes are not so easily expressed. One might say that navigating through an emotionally laden situation is similar to hitting a perfect kill shot in a racquetball match. It may be difficult to describe the physical movements, technical motions, and timing that goes into a successful shot, but it can be an easy task to do in the moment (i.e., given the appropriate past experiences are present to influence future performance). In an emotional situation, it can be difficult to describe, step by step, all of the processes associated with comprehending and effectively responding. However, in the moment accounting for all the cues in the

environment and acting appropriately seems to be a fairly natural and effortless process.

Implicit Measures

The idea of measuring implicit cognitive process has been around for some time. In fact, F.C. Donders suggested the possibility when latency was born from discovering that the time it takes to perform mental computation reveals something fundamental about the way the mind works in 1850 (Lane, Banaji, Nosek, & Greenwald, 2007). Fast forward 150 years and one of the most prominent and widely used implicit measures is the Implicit Association Test (IAT) developed by Greenwald et al. (1998) to measure such implicit cognitive processes. The IAT has reported to have been used in more than 200 published papers, hundreds of conference papers, and more than 4.5 million administrations have been completed.

The IAT is designed to measure the "relative strength of association between pairs of concepts, labeled for pedagogical purposes as *category* and *attribute*" (Lane et al., 2007 p. 62). The IAT is built on the concept of implicit associations. These associations and automatic mental processes can provide insight into an individual's underlying beliefs and attitudes. Daniel Kahneman describes many of these implicit association in his book *Thinking, Fast and Slow*, (2011). Kahneman explains that there are two systems at work when the mind processes information, system 1 and system 2. System 1 is characterized as an automatic system that requires no effort when processing information. However, System 2 is much slower. System 2 processes information on an as necessary basis or "when mental activities demand it (p. 16)". Within system 1 lies implicit thoughts and cognitions whereas System 2 houses the explicit thoughts of which the

individual is consciously aware.

The significance of understanding the two-system theory lies in behavior – more specifically, which system has the greatest influence on behavior. At first glance one might find it intuitive to consider System 2 as the main driving force of exhibited behaviors. However, the theory implies that this is not the case at all. The two-system theory suggests that System 1 is the true champion of the arena where thoughts, feelings, impressions are effortlessly produced in ways that fuel explicit beliefs and the choices we make. That is, System 1 is home to all of the innate behaviors humans exhibit. Kahneman goes on to state that "System 1 has learned associations between ideas" and "it has also learned skills such as reading and understanding nuances of social situations (p. 17)."

This leaves the question – Can the processes of system 1 be measured? And if so, how? The IAT measures the strengths of associations between concepts using latency (i.e., reaction times) and error rates (correct vs. incorrect categorizations) when sorting word or picture stimuli into paired categories. These pairings are presented in blocks – sets of the sorting task. Greenwald et al. (1998) provide an example of a prototypic 7-block IAT to illustrate this procedure using the target concepts of flowers and insects and a pair of evaluative attribute concepts – good and bad. An overview of the IAT structure can be seen in Table 1. Participants sit at a computer placing their left index finger on one key (usually E) and the right index finger on another key (usually I). These keys are then pressed as stimuli words are presented – one at a time – on the screen. In Block 1 participants complete practice trials of sorting various flower stimuli (Rose, Blossom, etc.) by hitting the left-hand key and insect stimuli (ladybug, praying mantis, etc.) by hitting the right-hand key. In Block 2, participants practice sorting good stimuli (superb,

glorious, etc.) by hitting the left-hand key and bad stimuli (painful, tragic, etc.) by hitting the right-hand key. In Block 3 the previous two tasks are combined so that flowers and good are paired for sorting (i.e., assigned to the same key) while insects and bad are paired together. Block 4 repeats the process presented in Block 3. Block 5 reverses the steps from Block 2 in that good stimuli are now assigned to the right-hand key and bad stimuli with the left-hand key. Similarly, Blocks 6 and 7 reverse the earlier pairings presented in Blocks 3 – flower and bad are sorted using the left-hand key, and insect and good are sorted using the right-hand key. Mean latency times are then compared between test blocks 4 and 7. In this IAT, a participant that sorts stimuli more quickly, and with fewer errors, when flowers are paired with good and more slowly when flowers are paired with bad, is said to be demonstrating an automatic (implicit) preference for flowers. The larger the difference between mean latency times, the stronger the association or IAT effect (Lane et al., 2007).

Often IATs reveal strong associations between self-concept categories and positive attribute pairings as opposed to negative attribute pairings. According to Schnabel, Asendorpf, and Greenwald (2008) this can pose a problem of confounding influence of valence with semantic value when an IAT utilizes a self-referent category. Participants may identify more strongly with words that carry a positive valence (e.g., strong) than with words that carry a negative valence (e.g., weak). To test this notion, Schnabel et al. controlled for valence (positive or negative) and discovered that self-descriptive attributes were more strongly associated with one's self-concept than non-self-descriptive words of a similar valence (2008). This finding highlights that when designing IATs one needs to not only focus on the semantic meaning of the word but the

valence as well. Instead of using a traditional bi-polar IAT, Schnabel et al. suggest using alternative formats - semantic contrasts that are non-bipolar – by creating balance between the paired concepts and the stimuli for their given dimension.

Table 1. Structure of the Implicit Association Test.

Block	Number of Trials	Left key response	Right key response
1*	20	Flower	Insect
2*	20	Good	Bad
3*	20	Flower + Good	Insect + Bad
4**	40	Flower + Good	Insect + Bad
5*	40	Insect	Flower
6*	20	Insect + Good	Flower + Bad
7**	40	Insect + Good	Flower + Bad

*Practice blocks; **Test blocks

Schnabel et al. (2008) provided examples of some non-bipolar balanced pairings such as: positive aspects of conscientiousness (disciplined, dutiful and determined) with positive aspects of agreeableness (amicable, warmhearted and docile) and an IAT featuring the negative aspects of each trait (chaotic, changeable and absentminded vs authoritarian, quarrelsome and egoistic). When assessing for convergent and discriminant validity amongst their measures the correlation coefficients supported the validity of the IATs. That is, the IATs measured implicit associations among semantically distinct constructs that were independent of self-esteem, and was done so in such a way that reflected relationships among explicit measures of corresponding constructs.

In accordance with the suggestions provided by Schnabel et al. as well as Oberdiear, Fischer, Fiscus, Willis, Stassen, and Miles (2016), researchers used trait descriptors related to EI attributes to develop IATs that are balanced with respect to an evaluative dimension, in order to not confound self-esteem with semantically distinct descriptors of EI behavioral tendencies. Four IATs were designed using pairing attributes developed from Goleman's (1995) four EI competency model of emotional intelligence (see Table 2) and attributes that are weakly associated with EI (physical strength and status).

Table 2. Goleman's (2001) Two-by-Two Model of Emotional Competencies

	Self (Personal Competence)	**Other (Social Competence)**
Emotional Recognition	Self Awareness • Emotional self-awareness • Accurate self-assessment • Self-confidence	Social Awareness • Empathy • Service orientation • Organizational awareness
Emotional Regulation	Self Management • Self-control • Trustworthiness • Conscientiousness	Relationship Management • Communication • Conflict management • Teamwork and Collaboration

Their study employed a multitrait-multimethod design (Campbel & Fiske, 1959) to examine the construct validity of the implicit measures and found considerable support for their convergent and discriminant validity. However, reliability estimates for three of the four IATs indicated that they were contaminated by excessive amounts of

measurement error (reliability coefficients were .45, .58 and .66), well below Nunnally and Bernstein's (1978) standard for adequacy. The present study sought to revise the EI IATs that Oberdiear et al. (2016) developed in an effort to improve their psychometric properties and then examine the construct validity of the revised measures.

Hypothesis

IAT measures of four EI attributes (Emotional Composure, Emotional Awareness, Emotional Support and Emotional Self-knowledge) will be related to corresponding explicit (self-report) measures of these attributes, and these relationships will be stronger than the relationships with both explicit (self-report) and implicit (IAT) measures of non-corresponding attributes.

This general hypothesis can be broken into more specific convergent and discriminant validity hypotheses. Furthermore, these more specific hypotheses can be evaluated by testing hierarchically nested latent trait models using confirmatory factor analytic (CFA) procedures in a manner described by Widaman (1985). These more specific hypotheses and procedures will be described below in the next section.

METHODS

Sample and Procedures

The Missouri State University Institutional Review Board's Protection of Human Subjects Committee approved this research (Appendix A) on October 19, 2017 (Study Number FY2018-146). Data were collected using Amazon's Mechanical Turk (MTurk) research participant recruitment system. The Human Intelligence Task (HIT) remained open approximately one week to allow workers to participate. Those who completed the HIT were provided a monetary incentive for their time. The HIT consisted of five IATs along with twelve explicit scales and a set of demographic questions. Participants initiated the study through a link to the Millisecond, Inc. website where all implicit, explicit, and demographic measures were administered through a single batch file. The order in which the measures were administered were: demographic items, the EI IATs, the NEO facet scale items, and the TEIQue items. Pilot study data suggested that it takes approximately 40 minutes to complete the administrations; however MTurk workers were provided a two-hour window before they were timed out. The final sample (N = 175) was further analyzed using SPSS statistical processes and the AMOS package.

Implicit Measures

This study relied on the IAT development guidelines put forth by Lane et al. (2007). All IATs utilized the standard seven block procedure and D-scoring method described by Greenwald, Nosek, and Banaji (2003). The original IAT method used the difference between the mean latencies from Test Blocks 4 and 7 (i.e., the mean for Block

7 minus the mean for Block 4). The D-scoring method used in this study uses an algorithm that incorporates practice trials and uses respondent latency variability to develop a standardized mean difference score. More specifically, the mean difference between Practice Blocks 3 and 6 is divided by the pooled standard deviation of the response latencies for these blocks. Similarly, the mean difference between the Test Blocks 4 and 7 is divided by the pooled standard deviation of the response latencies for these blocks. Finally, the two standardized mean differences are averaged. Among other benefits, Greenwald et al. (2003) provide evidence that the revised scoring procedure is resistant to artifacts related to subjects' overall speed of responding and is more internally consistent than the original metric. The IATs in this study followed the Oberdier et al. (2016) model for the global EI IAT: the target categories were good and bad – the same word stimuli used in the stock flowers vs insect IAT. The idea is to tap into one's personal values and assumes everyone has self-esteem. So, to the extent an individual exhibits a strong good + EI attribute association, we assume this person's implicit self-concept is more anchored in trait-EI. This follows the Greenwald et al. (2003) interpretation of the flower + good IAT.

For replication purposes, this study utilized Goleman's (2001) theory of emotional intelligence as the theoretical basis for EI. This two-by-two model (see Table 2) was used to construct four IATs, where one IAT represented each of Goleman's (2001) four EI competencies: Emotional Composure (regulation of one's own emotions), Emotional Self-Knowledge (recognition of one's own emotions), Emotional Awareness (recognition of others' emotions) and Emotional Support (regulation of others' emotions). A fifth global EI IAT was constructed by using a single stimulus item from

each of the four component competencies. Researchers used procedures described by Nosek, Greenwald, and Banaji (2005) to create EI IAT stimuli and category labels. Nosek et. al (2005) advise using a minimum of four stimulus items per category. Steffens, Kischbaum, and Glados (2008) suggest that using synonyms of the target categories is the most effective strategy to choosing stimuli.

Table 3. Category Labels and Stimuli for the Four Dimensions of EI

(Composure) Self-Control	**(Awareness) Aware**	**(Support) Helpful**	**(Self-Knowledge) Self-Aware**
Together	Perceptive	Caring	Introspective
Composed	Observant	Supportive	Reflective
Stable	Sensing	Attentive	Intuitive
Collected	Mindful	Understanding	Insightful

As previously mentioned, Schnabel et al. (2008) advise using valance-balanced stimuli to avoid confounding self-esteem with the targeted attributes. Following this advice, research team members were put through a word generating exercise. A stimulus category label was provided (e.g., Emotional Awareness) and the first four words that came to an individual's mind were recorded. Subsequently, team members' lists were checked for similarities within categories and differences across categories. Words with higher frequencies within each category were further compared using synonyms found at Thesaurus.com. After the stimuli were chosen, research team members ($N = 11$) chose four words from a list of six to eight words, per EI category, that they found most relevant to the target EI competency (e.g., Emotional Awareness). The research team (N

= 11) were put through a second word generation exercise to choose new EI category labels (Table 3, Table 4).

Two student volunteer samples (*N* = 174 and *N* = 59) were then used to pilot test four IATs – Two for each of the two external competencies of the EI model which had the poorest reliabilities in the Oberdiear et al. (2016) study. The mean classification error rates for the stimuli and the IAT score variance statistics from the pilot studies were used to create the final set of EI competency IATs.

Table 4. Category Labels and Stimuli for the Global-EI and Non-EI Competencies

Intelligence	**Individualism**
Relationships	Legacy
Empathy	Prestige
Poise	Reputation
Adaptability	Money

Explicit Measures

Personality. The NEO-PI-R (Costa & McCrae, 1992) provided scores on eight facet scales that theory and research (Petrides, Pita & Kokkinaki, 2007) suggest are related to the four components of Goleman's (2001) model of EI (see Table 2). Two facet scales were selected for each of Goleman's four EI competencies: O3-Feelings and E6-Positive Emotions (Self-awareness); N4-Self Conscious and N6-Vulnerable (Self-management); A3-Altruism and A6-Tenderminded (Social Awareness); E2-Gregarious

and E3-Assertive (Relationship Management). These relationships are displayed in the CFA model labeled Model 1 in Figure 1.

Trait-Emotional Intelligence. The short form of the TEIQue (v1.50; Petrides & Furnham, 2001) provided four factor scales related to EI: Emotionality, Sociability, Self-control and Well Being. The factor scales are composites of 15 more basic scales which, in turn, are composed of responses to the measure's 30 items. Although the four TEIQue factors do not map onto the four components of Goleman's model in an isomorphic manner, each of Goleman's competencies is theoretically related to one or more of the TEIQue factors. These relationships are displayed in the CFA model labeled Model 1.

Data Analysis

CFA model comparisons were utilized for data analysis purposes. Convergent and discriminant validity were assessed by changes in fit statistics between each model (Widaman, 1985). The technique consists of using nested models. In the initial model (Model 1) method factors and trait factors are left to intercorrelate freely. Thereafter, Model 1 is compared to subsequent, more restricted, models.

The hypothesized model for this study is demonstrated in Figure 1. Model 1 consists of four correlated latent traits that represent the four trait-EI factors. Two correlated method measurement factors are used as well to represent both the implicit and explicit measures of the study. Figure 2 shows the second model. Model 2 is more restrictive in that it contains no latent traits for trait-EI. Figure 3 represents a more restrictive model of perfectly correlated traits and two freely correlated method factors.

Figure 4 represents a model containing four freely correlated latent trait factors and two uncorrelated method factors.

According to Widaman (1985) one should begin by comparing models 1 and 2. During this comparison, the fit statistics should exhibit a notable deterioration from model 1 to model 2. To the extent that this occurs, convergent validity is demonstrated due to model 2's lack of specified traits.

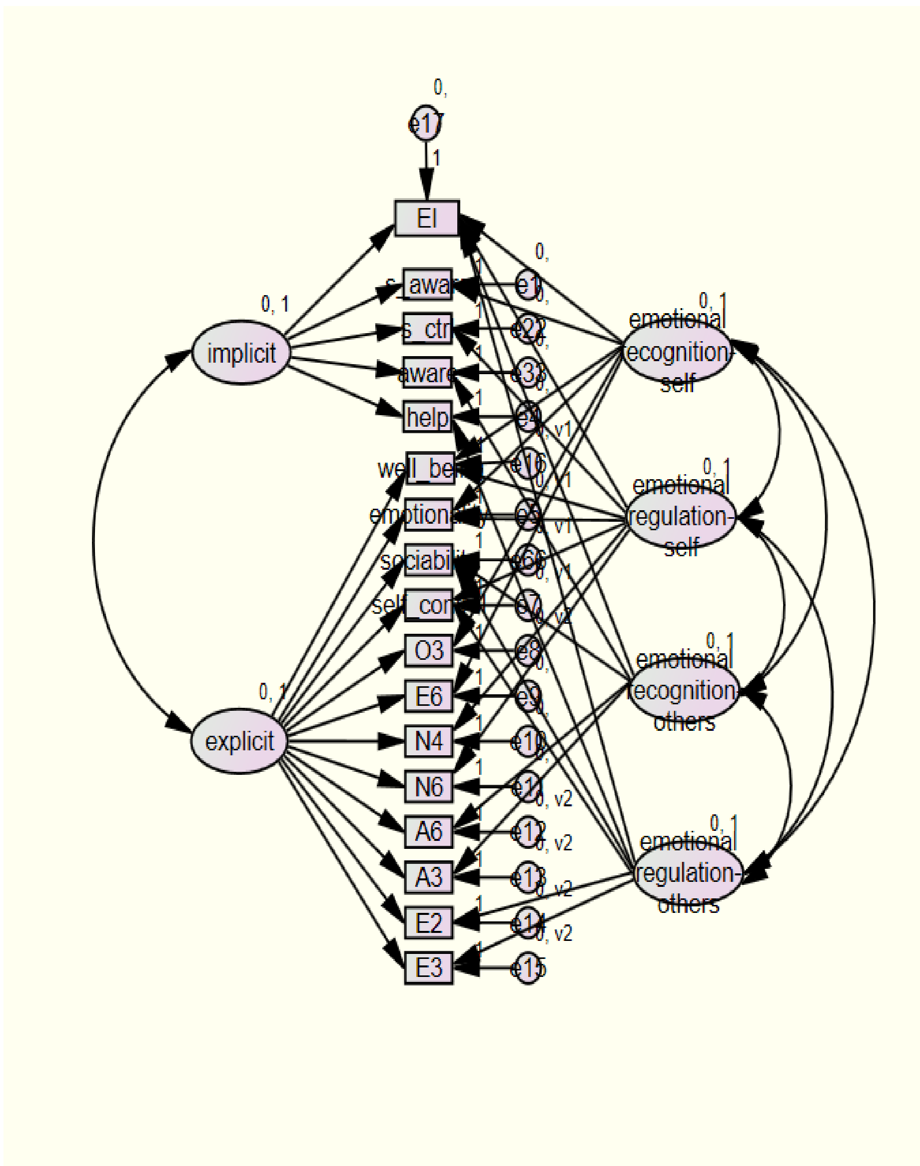

Figure 1.CFA Model 1: Two Freely Correlated Factors and Four Freely Correlated Factors

The second step compares models 1 and 3. Discriminant validity is demonstrated by diminished model fit statistics between freely correlated traits (Model 1) and perfectly correlated traits (Model 3).

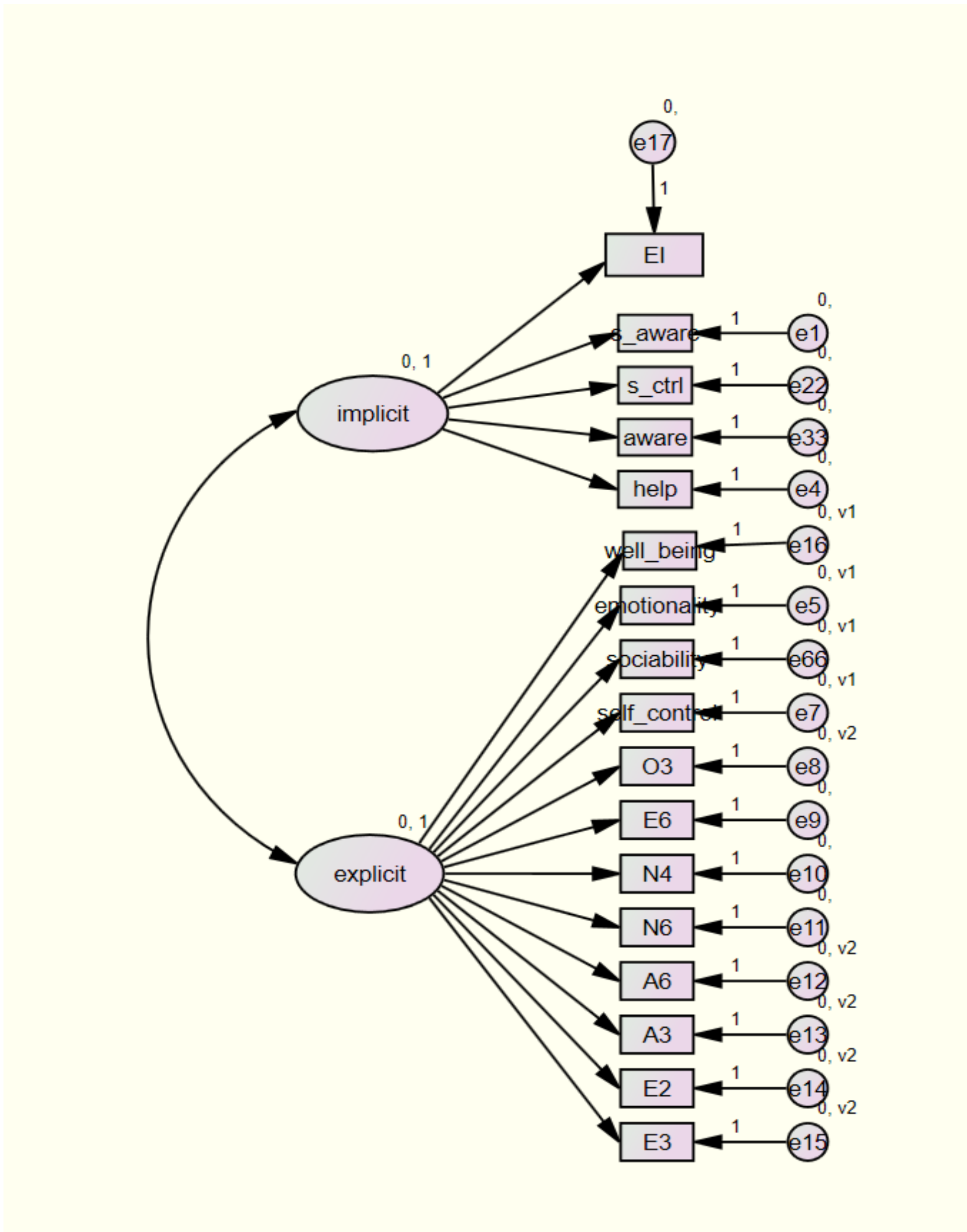

Figure 2. CFA Model 2: Two Freely Correlated Method Factors and No Trait Factors

However, due to the four trait-EI factors correlating amongst themselves, large discrepancies are not expected. The final step compares models 1 & 4. This step is similar to the previous, but with the method correlation removed.

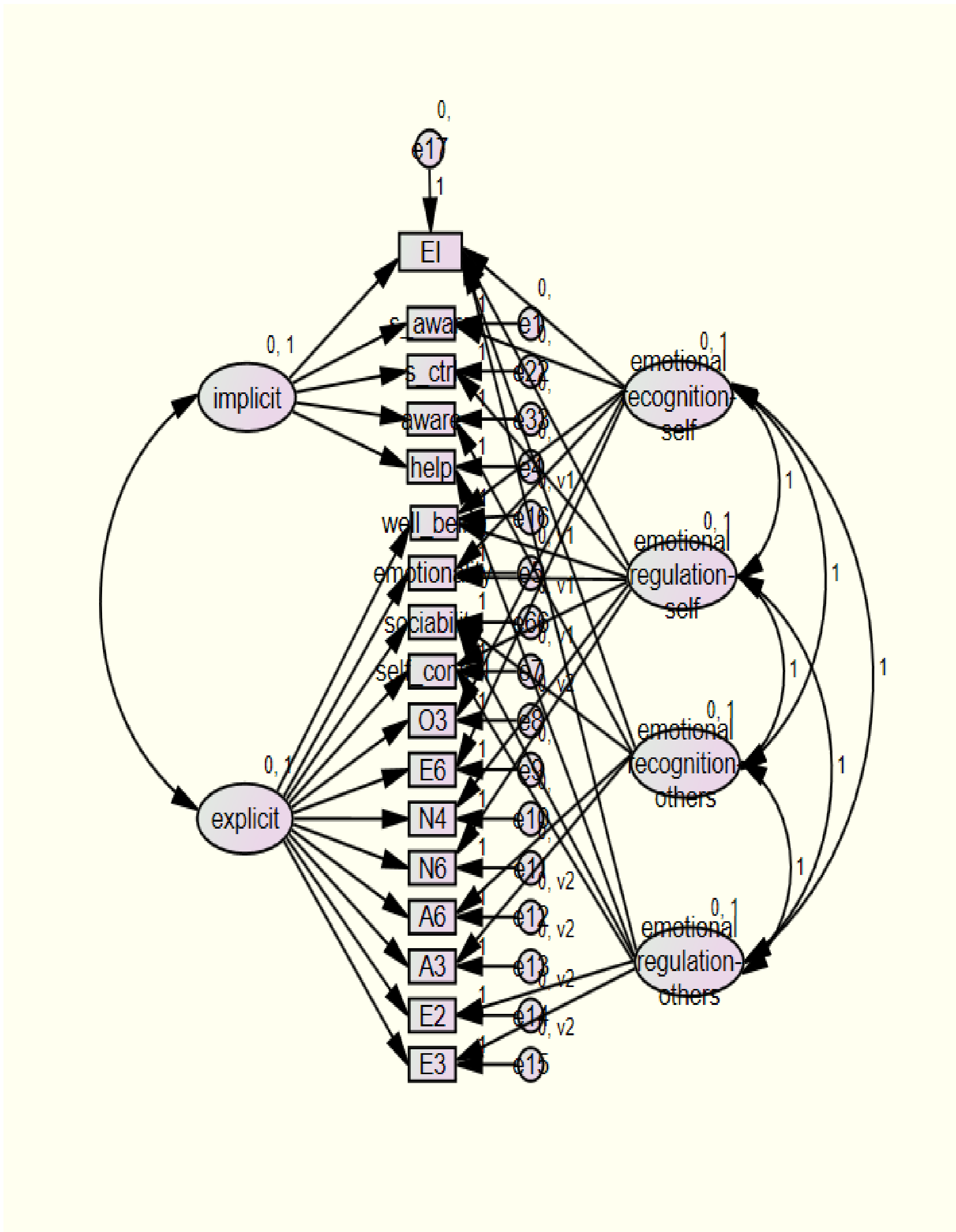

Figure 3. CFA Model 3: Two Freely Correlated Method Factors and Four Perfectly Correlated Trait Factors

Discriminant validity is demonstrated in the event that model 1 and model 4 do not differ in how well they fit the data (i.e., no cross-methodological bias).

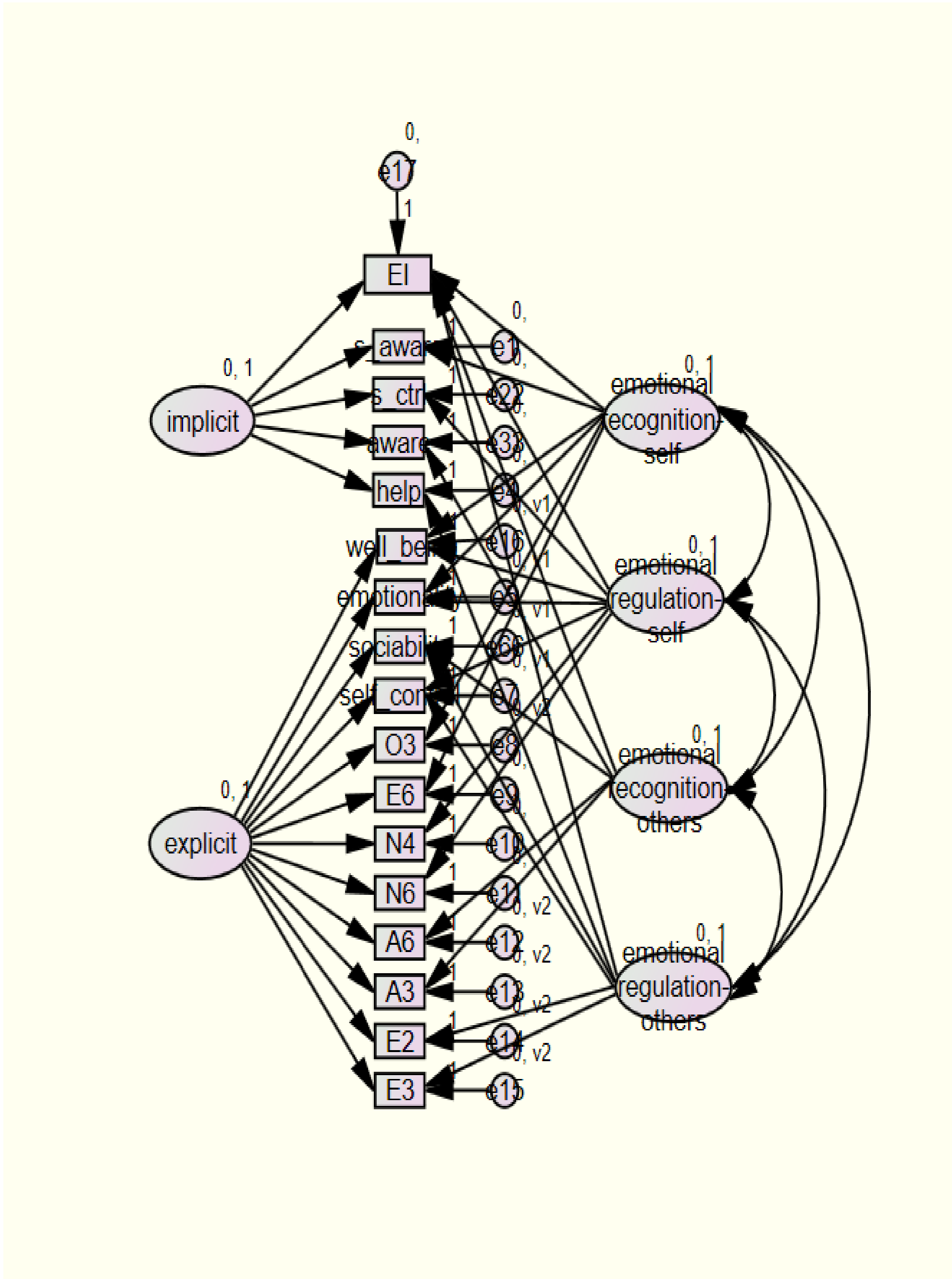

Figure 4. CFA Model 4: Two Uncorrelated Method Factors and Four Freely Correlated Trait Factors

RESULTS

Descriptive Statistics

The use of Amazon's MTurk system resulted in quite a large number of participants. The number of MTurk Workers that initiated the study totaled 701 individuals. However, after narrowing the subject pool to those who completed all measures, only 326 participants remained. The 326 participants were then screened based on the validity of their IAT scores. Those with misclassification error rates in excess of 25% were considered to have invalid scores. Pilot data suggested that mean error rates for subjects who were conscientiously engaged in the sorting tasks were about 10%, with well over 90% of pilot subjects having mean error rates below 25%. This left a sample of 175 individuals. The final sample was 65% female, with a mean age of 40.2, mean of 18.1 years of employment and 74% self-identified as United States citizens. Sample racial demographics were as follows: 1% American Indian or Alaskan Native, 3.5% Black or African American, 3.5% Two or More racial groups, 5% Hispanic or Latino, 24% Asian and 63% Non-Hispanic White.

Table 5 and Table 6 contain descriptive statistics for the study variables based on the final participant sample ($N = 175$). An a priori power analysis (MacCallum, Browne & Sugawara, 1996) indicated that the sample exceeded the number required to attain adequate power (.80), given the context of a null hypothesis of close fit (H_0: RMSEA = .05) and an alternative hypothesis of poor fit (H_A: RMSEA = .10).

Test of Hypothesis

Widaman (1985) uses model fit statistics comparisons for a set of nested CFA models to assess convergent and discriminant validity. The first comparison (Model 1 vs Model 2) demonstrates convergent validity to the extent that model deterioration occurs (i.e., poorer fit statistics). The second model comparison (Model 1 vs Model 3) demonstrates discriminant validity to the extent that model fit statistics differ between the freely correlated model (Model 1) and the perfectly correlated model (Model 3). The final comparison (Model 1 vs Model 4) uses the same logic as the Model 1-Model 3 comparison, but with the method correlation removed.

Table 5. Descriptive Statistics for Study Variables

Variables	N	Min	Max	Mean	SD	Alpha
Implicit Measures						
Aware	175	-.47	1.18	.33	.32	.76
Helpful	175	-.41	1.35	.32	.31	.73
Self-Aware	175	-.70	1.33	.27	.31	.74
Self-Control	175	-.45	1.11	.27	.29	.76
Global-EI	175	-.77	1.24	.34	.40	.86
Explicit Measures						
N4-SelfConscious	175	8	40	23.03	5.76	.79
N6-Vulnerable	175	8	36	18.64	5.73	.86
E2-Gregarious	175	8	35	22.18	6.38	.84
E3-Assertive	175	11	36	23.25	5.14	.77
E6-Pos. Emotions	175	14	38	27.94	5.23	.77
O3-Feelings	175	19	40	30.14	4.35	.74
A3-Altruism	175	17	40	31.74	4.48	.78
A6-TenderMinded	175	16	40	30.53	4.22	.65
Sociability	174	1.50	7.00	4.73	.85	.75
Self-Control	174	2.00	7.00	4.71	.98	.79
Emotionality	174	3.25	7.00	5.12	.89	.81
Well Being	174	2.50	7.00	5.19	.91	.78

Table 6. Zero-Order Correlations for Study Variables

Variables[1]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Implicit																
Aware	-															
Helpful	.65**	-														
Self-A	.63**	.68**	-													
Self-C	.64**	.70**	.69**	-												
Global	.59**	.56**	.57**	.51**												
Explicit																
N4	-.02	-.00	.01	.01	.053	-										
N6	-.05	-.11	-.11	-.09	-.10	.74**	-									
E2	-.16*	-.11	-.04	-.13	-.17*	-.33**	-.27**	-								
E3	-.05	-.08	.00	-.11	-.06	-.58**	-.54**	.43**	-							
E6	.010	.15	.05	.07	.10	-.38**	-.40**	.40**	.39**	-						
O3	.24**	.25**	.19*	.20**	.24**	.032	-.05	-.01	.03	.44**	-					
A3	.11	.29**	.13	.18*	.12	-.25**	-.31**	.16*	.11	.44**	.52**	-				
A6	.18*	.28**	.07	.15	.19*	-.06	-.16*	-.02	-.06	.20**	.40**	.58**	-			
Sociab	.03	.14	.08	.03	.01	-.59**	-.64**	.23**	.60**	.41**	.26**	.44**	.19*	-		
Self-C	.12	.21**	.16*	.16*	.12	-.68**	-.83**	.21**	.43**	.41**	.15	.42**	.28**	.64**	-	
Emot	.20**	.29**	.18*	.17*	.19*	-.28**	-.40**	.14	.22**	.53**	.66**	.69**	.49**	.52**	.51**	-
Well	.06	.14	.09	.08	.11	-.60**	-.68**	.32**	.41**	.56**	.21**	.46**	.20**	.61**	.72**	.54**

* $p < .05$; ** $p < .01$

[1] Variable names have been shortened due to space restrictions. All variables names are as follows: Implicit Measures, Aware, Helpful, Self-Aware, Self-Control, Global-EI, Explicit Measures, N4-Assertive, E6-Positive Emotions, O3-Feelings, A3-Altruism, A6TenderMinded, Sociability, Self-Control, Emotionality, Well Being.

Given that the method factors are expected to be uncorrelated, a null finding is predicted. Table 7 displays the fit statistics for each CFA model. The table results indicate that the initial hypothesized latent trait model proposed in Model 1 fits the variance-covariance structure of the MTMM data very well. The CFI value is greater than .90 and the RMSEA is less than .08 in accord with the recommended values (Bentler, 1990; Byrne, 2010). Additionally, we can conclude that the model is not a poor fit according to guidelines described by MacCallum et al., (1996). The 90% confidence interval for the RMSEA statistic is quite narrow and the upper bound falls below the threshold (.10) for a poor fit. The results in Table 8 provides substantial support for both convergent and discriminant validity for the hypothesized model given significant fit statistics deterioration occurs when compared to Model 2 and Model 3. More specifically, the CFI and RMSEA values from Model 1 to Model 2 offer considerable support for the convergent validity hypothesis (i.e., method variance does not solely explain the observed relationships among the measures).

Table 7. Summary of Goodness-of-Fit Statistics for CFA Models

Model	χ^2	df	CFI	RMSEA	90%C.I.
1. Freely correlated traits; freely correlated methods	174.22	95	.95	.069	.053, .085
2. No traits; freely correlated methods	622.52	110	.69	.164	.151, .176
3. Perfectly correlated traits; freely correlated methods	390.44	108	.84	.123	.110, .136
4. Freely correlated traits; uncorrelated methods	176.15	96	.95	.070	.053, .085

Similarly, empirical support for discriminant validity evidence is also demonstrated by Table 8 with the Model 1- Model 3 comparison. That is, when EI is condensed into a single factor, the model does a poor job of describing the relationships among the observed variables. More specifically, From Model 1 to Model 3 the CFI and RMSEA values fall from .95 to .84 and .069 to .123 respectively. As with Model 2, the statistics for Model 3 fall well outside the accepted thresholds for a good fit. The final comparison between Model 1 and Model 4 indicates the two method factors are unrelated and that there is no method bias across the two sets of measures (i.e., fit statistics are virtually identical).

Table 8. Differential Goodness-of-Fit Statistics for Nested Model Comparisons

Model Comparisons	$\Delta\chi2$	df	ΔCFI
Test of Convergent Validity			
Model 1 vs. Model 2	448.3*	15	.26
Tests of Discriminant Validity			
Model 1 vs. Model 3	216.12*	13	.11
Model 1 vs. Model 4	1.93	1	.001

*$p < .01$

Table 9 displays the loadings for each observed measure on the four EI trait factors and the two method factors of Model 1. The results demonstrate that most indicator variables for each factor had significant loadings (28 out of 36), providing further support for the construct validity of the measures. However, an important exception to this conclusion is the fact that none of the five IATs exhibited significant loadings on their corresponding EI traits. Although the global IAT had non-trivial

loadings on three of the four latent traits, the significance levels did not meet conventional standards (*p* values ranged from .11 to .17). This is likely due to all five of the IATs loading heavily on the corresponding (implicit) method factor.

Table 9. Trait and Method Loadings for CFA Model 1

	Emotional Rec (self)	**Emotional Reg (self)**	**Emotinl Reg (other)**	**Emotnl Rec (other)**	**Implicit**	**Explicit**
Implicit Measures						
Self-Aware	-.048				$.828^{***}$	
Self-Control		-.051			$.819^{***}$	
Helpful			.004		$.832^{***}$	
Aware				-.010	$.785^{***}$	
Global-EI	.322	-.193	-.348	-.026	$.665^{***}$	
Explicit Measures						
E6PosEmotion	$.525^{***}$					$.514^{***}$
O3Feelings	$.784^{***}$					-.010
Emotionality	$.733^{***}$	$-.268^{***}$				$.244^{**}$
Wellbeing	$.276^{***}$	$-.509^{***}$				$. 584^{***}$
N4SelfConscious		$.487^{***}$				$-.653^{***}$
N6Vulnerable		$.699^{***}$				$-.599^{***}$
Self-Control		$-.773^{***}$	-.071			$. 485^{***}$
E2Gregarious			$-.543^{***}$			$.721^{***}$
E3Assertive			$.267^{**}$			$.798^{***}$
Sociability			$.437^{***}$	$.464^{**}$		$.610^{***}$
A3Altruism				$.790^{**}$		.150
A6Tenderminded				$.731^{**}$		-.118

* $p < .05$; ** $p < .01$; *** $p <.001$

DISCUSSION

The purpose of this research was to investigate the validity of implicit measures designed to target attributes related to trait emotional intelligence. More specifically, this study sought to build upon previous research regarding IATs designed to measure trait-EI, enhancing measure reliability and assessing construct validity of the new measures. Overall, the study did well to provide construct validity for both implicit and explicit measures of trait-EI. However, there are some potential construct validity concerns due to IAT trait-EI factor loadings. However, the hypothesized CFA model clearly captured the variance-covariance structure of the 17 observed variables according to fit statistics. Comparisons between the initial model and subsequent restricted models (e.g. a single EI trait factor in addition to the two method factors) exhibited deterioration in fit statistics during comparisons, providing substantial evidence of convergent and discriminant validity for the hypothesized model.

In the previous line of research (Oberdiear et al., 2016), two of the trait-EI IAT measures exhibited reliability coefficients well below the level that is considered acceptable (i.e., EA-IAT = .58 and ES-IAT = .45). This study's IATs had reliability coefficients well above the acceptable range that Nunnally and Bernstein (1978) describe (typically in the mid 70's), especially the overall trait-EI IAT, which had a reliability coefficient (.86) that was greater than all of the established explicit measures. Along with improvements in reliability, overall error rates improved as well. Previously, the average error rates for our four IATs ranged from 9% to 13%, but this has since improved to approximately 7% for individual EI factor IATs and 11% for the global trait-EI IAT.

Although the EI IATs average error rates remain greater than the average error rates for IATs targeting racial attitudes (obtained from the Project Implicit web site), which ranged from 4% to 6% this is a step in the right direction.

Despite success improving measure reliability, it is important to note that none of the four IATs exhibited substantial, significant loadings on their corresponding latent traits. Previously, the two IATs involving the emotional recognition factors (Self-awareness and Social Awareness) exhibited significant loadings on their respective IATs and the two IATs that targeted the emotional regulation factors (Self-management and Relationship Management) did not. These results suggest that our implicit and explicit identities are *less* concordant when it comes to both the way we view ourselves sensing and expressing emotions. This dissociation may indicate a potential for implicit measures to have incremental validity (relative to explicit measures) for the prediction of overt behavior related to these constructs (e.g., effectively managing one's emotions at work). Lane et al. (2007) suggests three direction for future research. The initial suggestion focuses on refining attribute labels so that they are more easily identifiable. The second suggests creating stimuli that are more easily and accurately associated with the given attributes. Finally, the third suggestion recommends comparison attributes with stimuli that are more semantically distinct from EI.

It is important to note concerns with using MTurk subject pools. Data cleaning provided evidence that 46% of the original subject pool did not conscientiously perform their HIT. For research that relies on MTurk subject pools this is a large red flag. For example, The Self-Aware IAT reliability would have fallen from .74 to .55. This reliability degradation would not have been a function of the measure itself, but the

participants not conscientiously engaging their HIT. MTurk studies should do their best to incorporate validity assessments of their manipulations as countermeasures for non-engaged MTurk workers.

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APPENDIX

Appendix A. Human Subjects IRB Approval

To:
Donald Fischer
Psychology

RE: Notice of IRB Approval
Submission Type: Initial
Study #: IRB-FY2018-146
Study Title: Development and Validation of Implicit Measures of Emotional Intelligence
Decision: Approved

Approval Date: Oct 19, 2017
Expiration Date: Oct 17, 2018

This submission has been approved by the Missouri State University Institutional Review Board (IRB) for the period indicated.

Federal regulations require that all research be reviewed at least annually. It is the Principal Investigator's responsibility to submit for renewal and obtain approval before the expiration date. You may not continue any research activity beyond the expiration date without IRB approval. Failure to receive approval for continuation before the expiration date will result in automatic termination of the approval for this study on the expiration date.

You are required to obtain IRB approval for any changes to any aspect of this study before they can be implemented. Should any adverse event or unanticipated problem involving risks to subjects or others occur it must be reported immediately to the IRB.

This study was reviewed in accordance with federal regulations governing human subjects research, including those found at 45 CFR 46 (Common Rule), 45 CFR 164 (HIPAA), 21 CFR 50 & 56 (FDA), and 40 CFR 26 (EPA), where applicable.

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