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Emotional Resilience Emerges as Novel Aspect of Meta-Mood Experience: A Confirmatory Factor Analysis Accounting for Data Censoring
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Emotional Resilience Emerges as Novel Aspect of Meta-Mood Experience: A Confirmatory Factor Analysis Accounting for Data Censoring

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Abstract

Meta-mood experience refers to the thoughts and feelings that serve to monitor, evaluate, and at times change mood. The Trait Meta-Mood Scale (TMMS) was designed to gauge meta-mood experience along three factors: Attention, Clarity, and Repair. Previous factor analyses have verified this three-factor structure. However, one study by Palmer and colleagues found strong support for a four-factor structure. In light of this discrepancy, the present study aimed to replicate Palmer and colleagues' study in a new sample, comparing the models they used to determine which is best-fitting. We also aimed to correct the effect of data point censoring when estimating the factor models. Data point censoring occurs when researchers have only partial information about the value of a variable. Because no previous research has explored the TMMS while accounting for potential censoring, we aimed to test this idea in the current sample. A total of 202 undergraduates completed the TMMS during an online study. To compare the models, we relied on Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). Results revealed that the four-factor model fit the data better than the three- and one-factor models tested. In the four-factor model, the first three factors corresponded to the previous Attention, Clarity, and Repair factors. We named the fourth factor Emotional Resilience because the items loading on this factor suggested resistance to negative emotional experiences. We suggest TMMS users calculate scale scores based on all four of these factors to provide a more detailed description of meta-mood experience.

Keywords: Emotional intelligence, meta-mood, Trait Meta-Mood Scale, factor structure, censoring, CFA

Emotions occur as a response to internal thoughts or personally significant events in the environment (Lazarus, 1991). They can be a critical source of information, influencing how we interact and engage with the world. Emotional intelligence refers to one's ability to identify and monitor emotions and to use that emotional information to guide thoughts and actions (Salovey & Mayer, 1990). The purpose of this article is to re-examine the factor structure of one popular measure of emotional intelligence called the Trait Meta-Mood Scale.

The Trait Meta-Mood Scale: The Trait Meta-Mood Scale (TMMS) was designed to measure an aspect of emotional intelligence called the meta-mood experience (Salovey et al., 1995). Meta-mood experience refers to the thoughts and feelings that serve to monitor, evaluate, and at times change emotions and moods (Mayer & Gaschke, 1988). The TMMS divides meta-mood into three dimensions: attention, clarity, and repair. These dimensions correspond to an individual's perceived ability to attend to their moods, clearly experience their moods, and repair their negative moods, respectively.

Meta-mood experience is associated with the successful management of stress and increased life satisfaction (Extremera et al., 2009; Martinez-Pons,

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1997; Salovey et al., 2002). Individuals high in the TMMS dimension of emotional repair tend to use active coping strategies in response to stress and tend to experience lower levels of rumination (Salovey et al., 2002), a coping strategy that is consistently implicated in poor health outcomes (Nolen-Hoeksema et al., 1994). Additionally, higher levels of emotional clarity and emotional repair are associated with reduced stress and increased life satisfaction (Extremera et al., 2009).

Salovey et al. (1995) conducted a confirmatory factor analysis (CFA) to verify the factor structure of the TMMS in a sample of university students. CFA is a theory-driven statistical approach in which a researcher examines whether a set of data fits a hypothesized factor structure, and it is typically used to provide statistical support for the factors that underlie a measure (Kline, 2016). Using CFA, Salovey and colleagues found support for a three-factor structure of the TMMS. These factors directly corresponded to the dimensions of attention, clarity, and repair identified by Mayer and Gaschke (1988). This factor structure has also been shown to fit Korean, Portuguese, and Chinese versions of the 30-item TMMS (Lee & Lee, 1997; Li et al., 2002; Queirós et al., 2005).

However, a study by Palmer et al. (2003) found strong support for a four-factor structure. See Appendix A. They administered the TMMS to a sample from the Australian general population (n = 310) and tested a one-factor model, an oblique exploratory three-factor model (which was similar, but not identical, to Salovey et al.'s original three-factor model), and an exploratory oblique four-factor model. Both the three- and four-factor models explained the data well, with the four-factor model fitting better (comparative fit index [CFI] for the four-factor model was higher, .986 as opposed to .980; and root mean square error of approximation [RMSEA] was lower, .057 as opposed to .067).

In the four-factor model, the first three factors correspond to the three dimensions of meta-mood experience mapped out by Salovey et al. (1995). We named Palmer et al.'s (2003) fourth factor Emotional Susceptibility because the two items that loaded only on this factor (Item 14: My beliefs and opinions always seem to change depending on how I feel; and Item 9: When I am upset I realize that the "good things in life" are illusions) reflect the influence of moods on an individual's worldview and the tendency of an individual to fall prey to their emotions.

Palmer et al. (2003) attributed the differences in the factor analysis results to differences in the samples: Salovey et al. (1995) used American participants, whereas Palmer et al. used Australian participants. Others have noted that differences in participants can contribute to differences in factor analysis results (Velicer & Fava, 1998). Therefore, we decided to study the factor structure of the TMMS in a new sample. We also aimed to extend previous research on the TMMS by accounting for data point censoring when estimating the factor models, something that no published research to date has done.

Data Point Censoring: When a data point is censored, its value is only partially observed, so the researcher knows only that the data point is above or below some number, not its exact value (Gijbels, 2010). Censored data may occur when measures fail to distinguish between people on the low end or the high end of a dimension, such that scores on the measure do not capture the full variability on the dimension of interest. Left censoring occurs when low scores on a measure do not distinguish between people on the low end of a dimension. For example, consider an item that states, "No matter what happens, I remain optimistic", with response options of 1 = disagree, 2 = neutral, and 3 = agree. This item, which is designed to measure the ability to remain optimistic in the face of adversity, is highly susceptible to left censoring. Many people would likely disagree with this item and get a score of 1. Those people could nonetheless vary substantially in how optimistic they are: Some people might remain optimistic after some events, and some people might never feel optimistic. If so, scores would not accurately reflect the full variability on the dimension of interest, and left censoring has occurred.

Within psychology, censoring is relatively unrecognized, and researchers routinely neglect to correct for its effects. This negligence may lead to biased estimates of correlations and other related test statistics (Pesonen et al., 2015). This bias should be of concern to researchers carrying out CFAs to describe the structure of a set of items, because if censoring is unaccounted for, factor structures are likely to be inaccurate.

Purpose and Research Question: The present research examined the factor structure of the TMMS, while

correcting for possible censoring. We aimed to answer the following research question: When we take into account that some of the Trait Meta-Mood Scale items are censored, is a one-factor, Salovey et al.'s (1995) three-factor, or Palmer et al.'s (2003) four-factor model a better fit to the data? These models are shown in Appendix B.

Method

Participants: A total of 202 students were recruited from the psychology subject pool at University of Nevada, Las Vegas. Participants were required to be 18 years of age to be eligible for the study. The sample consisted of 137 females and 65 males, and they ranged in age from 18 to 49 years (M = 22.70, SD = 6.29). One of the participants did not state their age. Demographic data showed 116 of the participants identified as Caucasian (57.43%), 20 as African American (9.90%), 20 as Hispanic (9.90%), 32 as Asian (15.84%), one as Native American (.50%), and 13 as other (6.44%).

Measures:

Demographics

Participants reported their sex, age, and ethnicity.

Trait Meta-Mood Scale

The TMMS was designed to measure stable individual differences in the meta-mood experience. The measure consists of 30 items grouped into three scales: Attention, Clarity, and Repair. Each item is rated on a 5-point agreement scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

Procedures: Participants completed the demographic measure and the TMMS online as part of a larger study. They completed these measures on a computer during the first of two testing sessions. This session lasted for 1.5 hours and was not supervised. To minimize distraction and increase standardization, participants were encouraged to use computers in the university computer labs.

Data Analysis: We estimated and evaluated the fit of the one-, three-, and four-factor models using the lava package in R (Holst & Budtz-Jørgensen, 2013). Although several programs and R packages can be used to estimate CFA models while correcting for the effects of censoring, Holst et al. (2015) demonstrated that lava's estimates were less biased and more precise than the limited information estimator proposed by Muthén (1984) when estimating a complex structural equation model.

To identify which items may have censored values, we examined histograms and noted which items had an abundance of responses on the lowest end or the highest end. These analyses revealed that three items intended to measure the dimension of attention (Salovey et al., 1995) – Item 3 (I don't think it's worth paying attention to your emotions or moods), Item 4 (I don't usually care much about what I'm feeling), and Item 27 (Feelings are a weakness humans have) ¬– had an abundance of responses on the lowest end (98/202 for Item 3, 79/202 for Item 4, and 73/202 for Item 27). To judge whether left censoring could explain the large number of low scores, we examined the content of these items and judged whether the lowest scores on the items reflect the lowest scores on the full dimension of attention. Consider Item 4 (I don't usually care much about what I'm feeling): People who strongly disagree with this item may still vary in how much they care about their feelings: some may care a little and some may care a lot. This suggests that censoring may have occurred on this item. Similarly, when reading Items 3 and 27, we judged that left censoring may have occurred.

After specifying the censored items in lava, we estimated the one-, three-, and four-factor models and obtained goodness-of-fit statistics. Because lava does not report an omnibus chi-square test or other measures of absolute fit for models with censored ordinal data (K. Holst, personal communication, July 14, 2021), we relied on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to compare the models. The better-fitting model is the one that explains the greatest amount of variation in the data using the fewest possible parameters (Akaike, 1973; Schwarz, 1978); this is the one with the lower AIC or BIC value (Bozdogan, 1987; Kuha, 2004).

Results

The factor loadings for the one-, three-, and four-factor models are shown in Appendices C, D, and F, respectively. The four-factor model had the lowest AIC and BIC values, indicating superior fit over the other models. See Appendix F.

Within the four-factor model, the first three factors corresponded to the dimensions of Attention, Clarity, and Repair, and all had positive inter-

correlations, consistent with previous research (Palmer et al., 2003; Salovey et al., 1995). The interpretation of the fourth factor was not as straight forward. Two items had salient loadings on only this factor. These were Item 9: When I am upset I realize that the "good things in life" are illusions; and Item 14: My beliefs and opinions always seem to change depending on how I feel. In our initial results, both items had positive loadings, just like they did in Palmer et al.'s (2003) research. We had initially labeled this factor Emotional Susceptibility. However, Emotional Susceptibility was negatively correlated with Attention, Repair, and Clarity, suggesting that this factor was measuring the lack of meta-mood experience. Therefore, we reversed this factor so that high scores captured high levels of meta-mood experience. We named the reversed factor Emotional Resilience. High scores on this factor indicate resistance to negative emotional experiences and the toughness to remain stoic in the face of adverse emotions.

Discussion

Our study compared the one-, three-, and four-factor models of the TMMS to determine which had the best fit. We partially replicated the methods used in Palmer et al.'s (2003) study, which tested a range of factor structures for the TMMS. Our research is unique in that we took into account the possibility of censored data when estimating the factor models, something that no other study of the TMMS, including Palmer et al.'s (2003), has done. We found the four-factor model fit the data best. We thus replicated Palmer et al.'s (2003) results, while accounting for censoring in the estimation procedure.

Like us, Palmer et al. (2003) found that the four-factor model fit better than the three-factor model. However, they argued that differences in samples between their study and Salovey et al.'s (1995) study could explain why the four-factor model fit better. Because of this, they discounted their results and opted to advocate the original three-factor solution. Our study contributes to the literature by providing additional evidence for the four-factor model in a new sample.

We named the novel fourth factor Emotional Resilience because the items that loaded on only this factor reflected an individual's resistance to negative emotional experience. The items loading on only Emotional Resilience (Item 9: When I am upset I realize that the "good things in life" are illusions, with a loading of -.69; and Item 14: My beliefs and opinions always seem to change depending on how I feel, with a loading of -.59) come from the Repair and Clarity factors in the original three-factor solution: Item 9 originally loaded on Repair, and Item 14 originally loaded on Clarity. In our view, these items are better indicators of Emotional Resilience than Repair and Clarity. For example, disagreeing with Item 9, as it is worded, seems to capture an individual who does not let their negative emotions dictate how they perceive the world, which to us is a clearer indication of resilience in the face of negative moods than of the ability to repair moods. Similarly, disagreeing with Item 14 seems to indicate a person who does not allow their emotions to determine their beliefs and attitudes; in other words, the person has a durable sense of self. This seems to capture Resilience better than Clarity.

Differences between the various aspects of meta-mood experience matter. For example, clarity mediates the relationship between attention and repair; that is, there is an indirect relation between attention and repair, which can be explained by clarity (Palmer et al., 2003). Perhaps one needs to attend to emotions to clearly experience them and understand emotions clearly to successfully repair them (Palmer et al., 2003). Similarly, we hypothesize that emotional resilience mediates the link between clarity and repair. In other words, perhaps one needs to experience emotions clearly to be resilient in the face of negative moods, and perhaps this resilience is required to change negative moods into positive ones. Future research could test this hypothesis.

Accounting for Emotional Resilience provides a more detailed description of meta-mood experience. Thus, TMMS users may wish to calculate scale scores based on all four factors in our model. To do so, three changes are needed. First, because item 12 was not included in the four-factor model, it should be excluded from scoring. Second, an Emotional Resilience scale score can be calculated using the two items that loaded uniquely on this factor (Items 9 and 14) and a third item that cross-loaded on Repair in the four-factor solution (Item 19). Third, the scoring of the Clarity and Repair subscales should be adjusted: Items 9 and 19 should be removed from the Repair subscale, and Item 14 should be removed from the Clarity subscale.

Future research could also explore the relation of Emotional Resilience to coping strategies (Lazarus & Folkman, 1984). We hypothesize that Emotional Resilience is related to improved emotional and social functioning and to greater use of adaptive coping strategies that allow one to successfully manage stressful encounters. Perhaps individuals who are emotionally resilient will be more likely to think rationally in the face of negative emotions; therefore, they will be unlikely to fall prey to those emotions and will potentially make use of adaptive coping strategies, such as problem-solving efforts in the face of stress, as well as more positive thinking (Lazarus & Folkman, 1984).

One limitation of the present study is that we did not use absolute measures of fit to examine the factor models, because the lava package does not provide these statistics for censored data models with ordinal data. AIC and BIC measure only relative fit. Thus, the four-factor model had better fit than the one- and three-factor models tested, but we do not know if it fit the data well. We suggest future researchers use other statistical programs to replicate (or extend) our study. One possible program is Mplus, which to our understanding reports absolute fit measures for censored data models.

Censoring is an important phenomenon that is too often overlooked in psychological research. When censoring occurs, it can distort the relationships between the measures and hence distort the results of any multivariate analyses that are based upon those relationships. Thus, it is important to take into account censoring when conducting multivariate analyses of psychological measures. This study contributes to this literature by examining the factor structure of the TMMS while correcting for the effects of censoring. It is our hope that future researchers conducting factor analyses of psychological measures will evaluate whether data points appear to have been censored and, if so, will use analyses that take that censoring into account.

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Appendix A: Table 1. Items with Salient Loadings in Four-Factor Model (Palmer et al., 2003)

Item
Clarity
5. Sometimes I can't tell what my feelings are.
6. I am rarely confused about how I feel.
11. I can never tell how I feel.
15. I am often aware of my feelings on a matter.
16. I am usually confused about how I feel.
20. I feel at ease about my emotions.
22. I can't make sense out of my feelings.
25. I am usually very clear about my feelings.
28. I usually know my feelings about a matter.
30. I almost always know exactly how I am feeling.
Attention
2. People would be better off if they felt less and thought more.
3. I don't think it's worth paying attention to your emotions or moods.
4. I don't usually care much about what I'm feeling.
7. Feelings give direction to life.
10. I believe in acting from the heart.
17. One should never be guided by emotions.
18. I never give in to my emotions.
21. I pay a lot of attention to how I feel.
23. I don't pay much attention to my feelings.
24. I often think about my feelings.
27. Feelings are a weakness humans have.
29. It is usually a waste of time to think about your emotions.
Repair
1. I try to think good thoughts no matter how badly I feel.
8. Although I am sometimes sad, I have a mostly optimistic outlook.
13. When I become upset I remind myself of all the pleasures in life.
19. Although I am sometimes happy, I have a mostly pessimistic outlook.
26. No matter how badly I feel, I try to think about pleasant things.
Emotional Susceptibility
8. Although I am sometimes sad, I have a mostly optimistic outlook.
9. When I am upset I realize that the "good things in life" are illusions.
14. My beliefs and opinions always seem to change depending on how I feel.
19. Although I am sometimes happy, I have a mostly pessimistic outlook.
21. I pay a lot of attention to how I feel.
24. I often think about my feelings.

Note. We named these factors based on the salient loadings.

Appendix B: Table 2. One-, Three-, and Four-factor Models for the TMMS

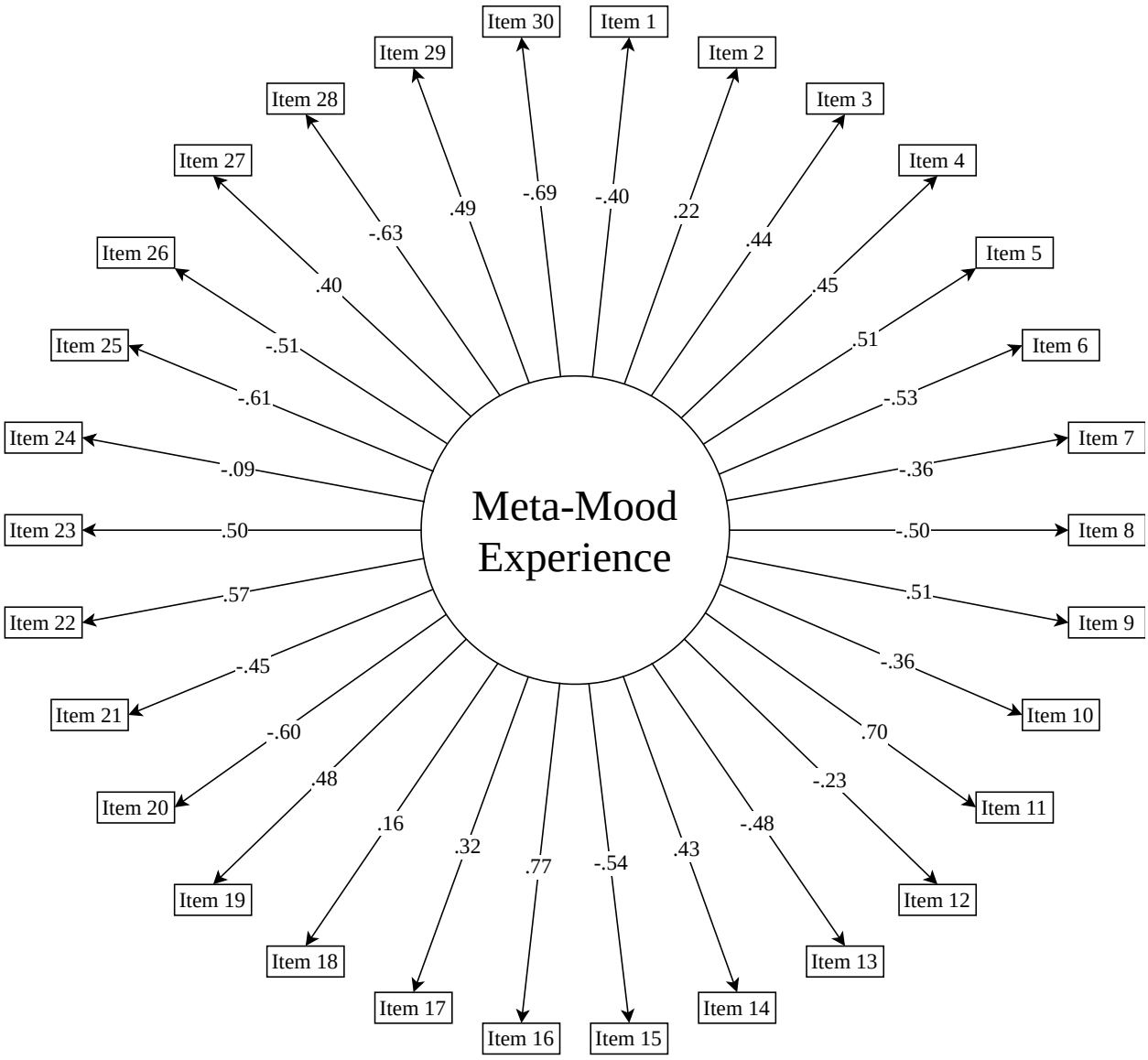
Item Number	One Factor	Three Factor [a]	Four Factor [b]
1	1	3	3
2	1	1	1
3	1	1	1
4	1	1	1
5	1	2	2
6	1	2	2
7	1	1	1
8	1	3	3, 4
9	1	3	4
10	1	1	1
11	1	2	2
12	1	1	—
13	1	3	3
14	1	2	4
15	1	2	2
16	1	2	2
17	1	1	1
18	1	1	1
19	1	3	3, 4
20	1	2	2
21	1	1	1, 4
22	1	2	2
23	1	1	1
24	1	1	1, 4
25	1	2	2
26	1	3	3
27	1	1	1
28	1	2	2
29	1	1	1
30	1	2	2

Note. The numbers in columns 2-4 indicate which of the four factors each item loaded on for that particular model. Item 12 is not included in the four-factor model because it did not have any salient loadings in Palmer et al.'s (2003) results.

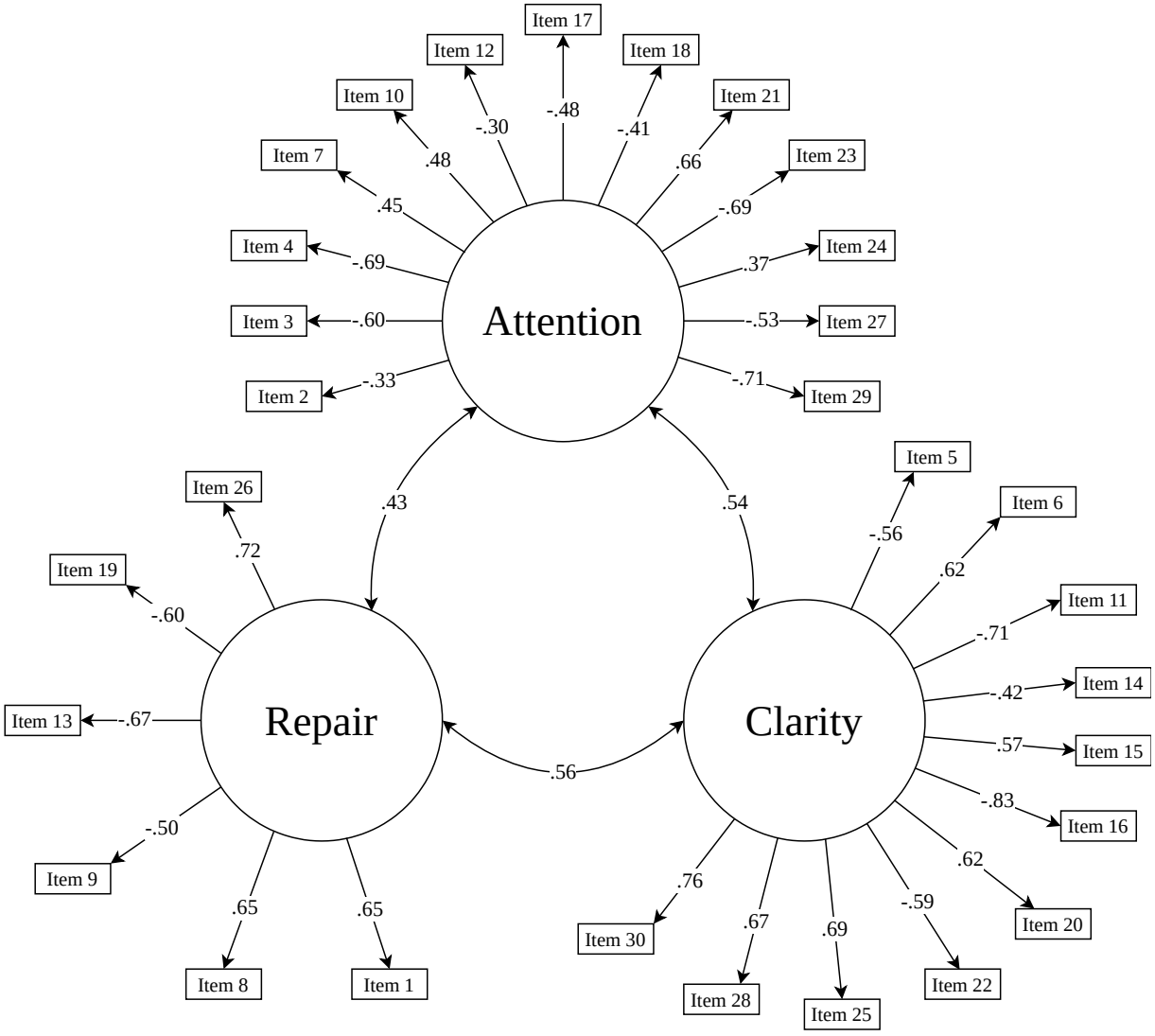
[a] Based upon Salovey et al.'s (1995) results. 1 = Attention; 2 = Clarity; 3 = Repair.

[b] Based upon Palmer et al.'s (2003) results. 1 = Attention; 2 = Clarity; 3 = Repair; 4 = Emotional Resilience.

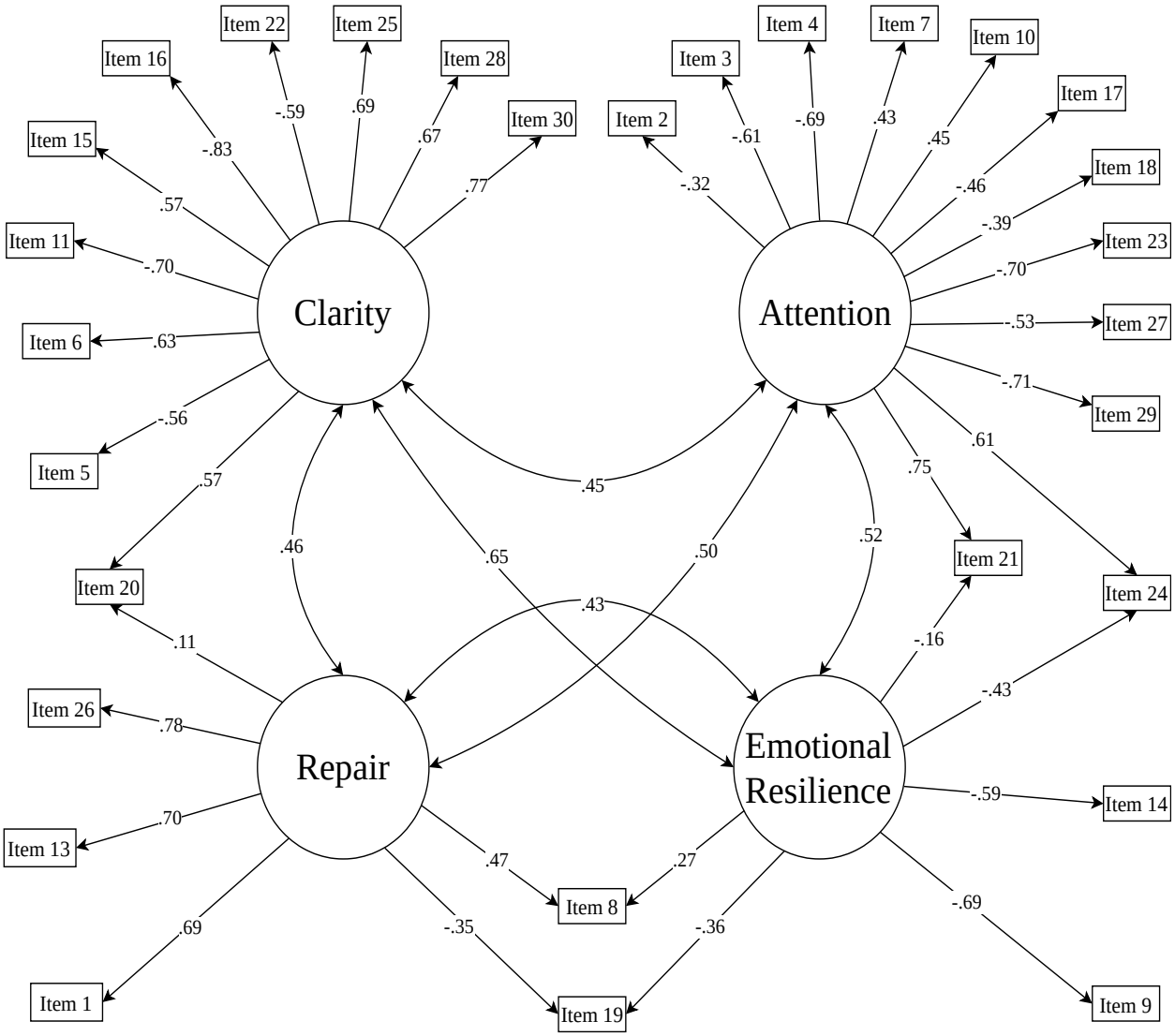
Appendix C: Figure 1. CFA Model Representing the General Factor (One-factor) Structure of the TMMS



Appendix D: Figure 2. CFA Model Representing the Three-Factor Structure of the TMMS from Salovey et al. (1995)



Appendix E: Figure 3. CFA Model Representing the Four-Factor Structure of the TMMS from Palmer et al. (2003)



Appendix F: Table 3. Fit Statistics for TMMS Factor Models

Model	AIC	BIC
One Factor	15067.46	15671.31
Three Factor	14583.70	15221.10
Four Factor	14021.00	14688.56

Note. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.