**Developing Facet-Level and Ultra-Brief MEAQ Short Forms Using Ant Colony Optimization**

Experiential avoidance is conceptualized as the tendency to avoid negative internal experiences even when doing so exacerbates distress in the long-term (Hayes et al., 1999; Gámez et al., 2011). A broad body of research implicates experiential avoidance as a transdiagnostic risk factor for the development and maintenance of psychopathology, as studies have found associations between experiential avoidance and (1) internalizing psychopathology, including depression, anxiety, obsessive-compulsive-related, and posttraumatic stress disorders (Akbari et al., 2022; Naragon-Gainey & Watson, 2018), (2) antagonistic externalizing psychopathology, including personality disorders (Hulbert & Thomas, 2010; Neacsiu et al., 2014), (3) disinhibited externalizing psychopathology, including substance use disorders (Forsyth et al., 2003; Shorey et al., 2017), (4) thought disorders, including the schizophrenia spectrum (O’Driscoll et al., 2014; Valiente et al., 2015), and (5) detachment-related psychopathology, including avoidant personality disorder (Lampe & Malhi, 2022; Spinhoven et al., 2009). Consequently, experiential avoidance has been included as a key construct to target in multiple treatment modalities, including the Unified Protocol for Transdiagnostic Treatment of Emotional Disorders (Barlow et al., 2013), Acceptance and Commitment Therapy (Kerns, 2011), Cognitive Behavioral Therapy (Espejo et al., 2017), Mindfulness-Based Cognitive Therapy (Creswell, 2017), and Dialectical Behavioral Therapy (Lynch et al., 2006).

Refining the measurement of transdiagnostic vulnerability factors such as experiential avoidance is critical, as a wealth of research has established that implementing transdiagnostic approaches to measurement results in a more reliable and valid assessment of psychopathology (Kotov et al., 2021; Stanton et al., 2020). More specifically, transdiagnostic frameworks such as the Hierarchical Taxonomy of Psychopathology (HiTOP; Kotov et al., 2017) and the Research Domain Criteria (RDoC; Insel, 2010) have been constructed with a quantitative approach to address psychometric limitations of the categorical taxonomies of psychopathology used by the DSM (APA, 1980, 1987, 1994, 2000, 2013, 2022), including pervasive comorbidity among the diagnostic system, diagnostic heterogeneity, and poor reliability of categorical disorders writ large due to dichotomization based on arbitrary thresholds for meeting diagnostic criteria (Chmielewski et al., 2015; Krueger et al., 2018; see Ringwald et al., 2021 for meta-analytic review).

There is a growing body of research on the measurement of experiential avoidance, with Acceptance and Action Questionnaire (AAQ-I; Hayes et al., 2004) and the revised versions of the AAQ-I (i.e., AAQ-II and AAQ-3; Bond et al., 2011; Ong et al., 2020) as the most widely used measure. However, there have been mixed findings regarding the psychometric properties of the AAQ measures, with some studies supporting the psychometric soundness of the measures (e.g., Fledderus et al., 2012; Gloster et al., 2011), and other studies finding unsatisfactory results (e.g., Bond & Bruce, 2003; Marx & Sloan, 2005; Rogge et al., 2019; Zvolensky & Forsyth, 2002).

It should be noted that a major limitation of the literature on the psychometric properties of the AAQ measures has been its piecemeal investigation vis-à-vis the construct validity of the two measures (the extent to which the measures assess the construct they intend to measure, i.e., experiential avoidance; Campbell & Fiske, 1959; Cronbach & Meehl, 1955; Loevinger, 1957). Construct validity serves as an overarching measure of validity comprising all indicators of reliability and forms of validity including content, criterion, convergent, and discriminant validity (see Strauss & Smith, 2009, for an overview of construct validity), and is not only essential for the evaluation of a measure’s psychometric soundness, but also for its clinical utility (Chmielewski et al., 2015; Clark & Watson, 2019). Accordingly, Rochefort and colleagues (2018) examined the construct validity of experiential avoidance measures and found that the AAQ-II provided an advantage over AAQ-I by demonstrating satisfactory levels of reliability, which is one of many components of construct validity (Chmielewski & Watson, 2009; Clark & Watson, 1995; Simms, 2008). This finding is consistent with other studies examining the reliability of the AAQ-I and the AAQ-II (e.g., Bond & Bunce, 2003; Correa-Fernández et al., 2020; Hayes et al., 2004, 2006). However, studies including Rochefort et al. (2018) have found convergent and discriminant validity of both the AAQ-I and AAQ-II to be problematic, specifically relative to measures of trait negative affect and neuroticism (e.g., Boelen & Reijntjes, 2008; Kashdan & Breen, 2007; Tyndall et al., 2019; Vaughan-Johnston et al., 2017; Wolgast, 2014).

The Multidimensional Experiential Avoidance Questionnaire (MEAQ; Gámez et al., 2011) was developed to address the aforementioned limitations of the AAQ measures by including different manifestations of experiential avoidance shown in the existing literature (see Chawla & Ostafin, 2007; Hayes et al., 1996; Malo et al., 2022), providing incremental validity above and beyond measures of distress. Unlike the AAQ measures, the MEAQ has a multidimensional structure comprising six dimensions of experiential avoidance: (1) *behavioral avoidance*, measuring situational avoidance of physical distress and discomfort; (2) *distress aversion*, measuring nonacceptance or negative perceptions of distress; (3) *procrastination*, measuring the degree to which one delays activities that may cause distress; (4) *distraction* or *suppression*, measuring the degree to which one attempts to suppress and ignore distress; (5) *repression* or *denial*, measuring dissociation and creating distance from distress; and lastly (6) *distress endurance*, which measures willingness to engage in activities that may be distressing in the short-term but adaptive in the long-term (Gamez et al., 2011). An individual with a high level of trait experiential avoidance as conceptualized by the MEAQ would be expected to show high levels of behavioral avoidance, distress aversion, procrastination, distraction/suppression, and repression/denial. Further, as distress endurance is expected to be negatively associated with experiential avoidance, an individual with a high level of experiential avoidance would be expected to show low levels of distress endurance. It is important to note that as the MEAQ was published more recently relative to the AAQ, a smaller body of literature has examined its psychometric properties. However, research to date has found that the MEAQ demonstrates optimal psychometric properties across different samples (e.g., Lewis & Naugle, 2017; Tyndall et al., 2019).

Given the frequent usage of the experiential avoidance measures in supporting core theoretical assumptions of Acceptance and Commitment Therapy (Hayes et al., 2004; Hayes & Pierson, 2005) and other third-wave behavioral treatment modalities (e.g., Eustis et al., 2020; Reddy et al., 2011; Roemer et al., 2008), the development and validation of such measures with good psychometric properties is an essential first step. The next step is to ensure that the measures have utility in different research and clinical settings in which the measured construct is of interest. With this respect to this aspect, the long-form of the MEAQ falls short with its 62-item length. In time-limited research and clinical settings, the length of administration time for self-report questionnaires have shown associations with greater participant and client burden (Eisele et al., 2020; Bodart et al., 2018; Galesic & Bosnjak, 2009; Rolstad et al., 2011).

To address this limitation, two abbreviated versions of the MEAQ have been developed to date. The Brief Experiential Avoidance Questionnaire (BEAQ), developed by Gámez and colleagues, selected items from the full MEAQ by conducting an exploratory factor analysis to retain 15 items based on the consistency and magnitude of factor loadings across three samples (Gámez et al., 2014). However, the resulting 15-item BEAQ does not contain subscales which limits the measure’s utility when researchers are interested in finer grained aspects of experiential avoidance. More recently, Sahdra and colleagues developed a 30-item short form of the Multidimensional Experiential Avoidance Questionnaire using Genetic Algorithm (MEAQ-30; Sahdra et al., 2016).

To date, factor analytic and response scale methods continue to be a common approach for developing short form measures of multidimensional constructs. However, studies have consistently shown that factor analytic and response scale methods such as confirmatory factor analysis (CFA) and item response theory (IRT) result in measures that capture the same latent construct as the full measure with abbreviated length, but with poor structural integrity at both the facet and item levels due to the restrictive conditions that are unsuitable for modeling multidimensional constructs with non-negligible cross-loadings (e.g., Church & Burke, 1994; McCrae et al., 1996). Less restrictive approaches such as exploratory structural equation modeling (ESEM) and item parceling have been shown to be successful at ameliorating this issue (Asparouhov & Muthén, 2009; Hall et al., 1999), but ultimately do so by obscuring––rather than resolving––poor model fit (Olaru et al., 2019; Sterba & Rights, 2022).

Meta-heuristic approaches address these limitations by allowing for optimization of multiple model fit criteria, enabling researchers to test all possible models (i.e., item combinations) with a computerized algorithm.

The two most popular metaheuristic algorithms, Ant Colony Optimization (ACO; Colorni et al., 1999) and Genetic Algorithm (GA; Yarkoni, 2010), have been repeatedly found to produce more psychometrically sound short scales when compared with more traditional (i.e., factor analytical and response scale) methods of short scale construction (e.g., Schroders et al., 2016). The classical AS approach to ACO identifies a subset of items of the full measure that are most indicative of the latent construct of interest by defining a fitness function that captures the goodness-of-fit of the abbreviated measure to the data, which is consequently used to evaluate the quality of solutions resulting from ACO. Subsequently, the ACO algorithm searches for the optimal subset of items by simulating the behavior of a group of artificial ants that follow pheromone trails that are updated based on the quality of the solutions found (Dorigo et al., 2006). Preliminary findings have yielded mixed results when comparing the GA and ACO based on the classical ant system (AS; Dorigo & Di Caro, 1999) approach (cf. Olaru et al., 2015; Schroeders et al., 2016).This discrepancy in this comparison across studies may be due to (1) differences in the optimization function used for GA and AS-based ACO, and (2) the underlying assumption for GA that the total score of the original scale is a valid representation of the construct, which does not hold for multidimensional constructs, and is not assumed by the ACO (Olaru et al., 2015; Schroeders et al., 2016).

However, the MAX-MIN Ant System (MMAS) and brute-force approaches to item selection with ACO offers several advantages over GA (Stützle & Hoos, 2000). The brute-force approach guarantees that the resulting solution of the search is optimal (i.e., as it involves testing and comparing all possible combinations; Schultze, 2017). Although probabilistic (and therefore not resulting in a guaranteed optimal solution), the MMASapproach to ACO improves upon the classical AS approach by (1) using the minimum pheromone level as its parameter to prevent the pheromone trails from evaporating completely, allowing the algorithm to maintain some of the information from previous iterations and avoid getting stuck in local optima, and (2) taking into account both the length of the solution path and the performance of the solution, allowing the algorithm to balance exploration and exploitation and find good solutions in a reasonable amount of time. In contrast, simple ACO uses a more simplistic formula for updating pheromone trails, which can sometimes lead to suboptimal solutions (Schultze, 2017; Stützle & Hoos, 2000). Likewise, GA does not allow for the maintaining information from previous iterations, and has a higher likelihood of finding suboptimal solutions (Olaru et al., 2015; Schroeders et al., 2016).

Given the aforementioned advantages and the need for short forms of the MEAQ in both research and clinical settings, the current study aims to develop and validate brief facet-level and ultra-brief short forms of the MEAQ using MMAS and brute-force approaches for item selection with ACO.