Mediating mechanisms of the relation between anxiety and cognitive control in Spanish-speaking young adults

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Dissertation Committee Certification

We certify that we have read this dissertation and that in our opinion it is adequate in scope and quality of its content for the degree of Doctor of Philosophy in Psychology with specialization in Academic-Investigative Psychology at the University of Puerto Rico, Río Piedras Campus.

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Introduction

For several decades, the scientific literature has focused on the direct effect of anxiety on cognitive control (Bar-Haim et al., 2007), paying less attention to the intermediate mechanisms underlying this relationship (Parmentier et al., 2019). Although there is an ever-increasing trend of research findings that show how anxiety negatively influences different aspects of cognitive control, such as cognitive interference towards emotional stimuli (Chen et al., 2013), reversal learning (Wilson et al., 2018), and task switching cost (Gul & Humphreys, 2014), there is still much to learn about the cognitive processes that have a mediating role in this relation. This is because traditional statistical models only examine the effects of independent variables on a dependent variable, while ignoring mediating variables that possibly influence these relationships. Consequently, this study focuses on understanding how these variables mediate the association between anxiety and cognitive control.

On the one hand, traditional research approaches aim to answer "if" or "whether" anxiety has an effect on cognitive control. The “if” or “whether” questions are most useful when a research topic is relatively new until a consistent trend is identified in the scientific literature (Hayes, 2018). In contrast, the approach used in this study examines “how” anxiety and cognitive control are causally linked, through various underlying cognitive and affective mechanisms. Therefore, “how” questions are useful to better comprehend the mechanisms that exerts mediating effects on the association between anxiety and cognitive control. Having a better understanding of these intermediary variables can be useful in the development of effective anxiety prevention programs (Freudenthaler et al., 2017).

The target population for this study were Spanish-speaking young adults between the ages of 18-29 years. The sample consisted of young adults because young adulthood is a risk period for the emergence of anxiety disorders. Although adolescence is considered a risk period, the study of young adults provides some methodological advantages. Young adults between the ages of 18-29 have reached maturity in their cognitive control abilities, compared to adolescents which are still developing these capabilities. Because of this, studying the mediating effects of the variables of interest in adolescents would be much more difficult. Thus, to measure in adolescents the mediating effects of intermediary variables in anxiety and cognitive control would require the study of smaller age ranges and significantly larger samples because of the variability in the development of cognitive and affective processes (Luna, 2009). Although this would be a relevant type of study, the magnitude of the sample would be beyond the scope of a doctoral dissertation project.

After examining the literature and identifying potential variables of interest, we proposed as a working hypothesis that a) cognitive flexibility, b) cognitive avoidance, c) decentering, and d) dispositional mindfulness have a mediating role on the association between anxiety and cognitive control in Spanish-speaking young adults. By examining the mediating roles of these intermediate variables, it will be possible to develop more comprehensive and informed interventions aimed at reducing anxiety. This study contributes to filling a gap in the scientific literature regarding the need to develop more complex models that examine the multiplicity of relations that may exist between the various variables.

Brief historical background of the direct effect of anxiety on cognitive control

In the early 1950s, the *Diagnostic and Statistical Manual of Mental Disorders* (1st ed.; DSM-1; American Psychiatric Association, 1952) considered anxiety as a danger signal sent and interpreted by the conscious aspect of the personality. However, this construct has experimented various changes in its conceptualization since then (Crocq, 2015). It is currently defined as an emotion characterized by feelings of tension, worried thoughts, and physical changes like increased blood pressure. Specifically, individuals with anxiety tend to have frequent intrusive thoughts, avoid situations that worry them, and present physical symptoms such as trembling, sweating, or a rapid heartbeat (VandenBos, 2015).

On the other hand, in the mid-1970s, Baddeley and Hitch (1974) developed one of the first frameworks to study cognitive control from a working memory perspective. These researchers explained how the central executive regulates where the individual focus its attention, allowing to use top-down processing. Other approaches of cognitive control have focused on examining specific abilities of the central executive. For example, Miyake and colleagues (2000) found that there are three executive functions: inhibition, shifting, and updating, which relate differentially to more complex behaviors. These findings were helpful in providing a more comprehensive understanding of cognitive control and the relation between emotion and cognitive processes (Grant & White, 2016).

Influenced by the findings of Miyake and colleagues (2000), Eysenck and coworkers (2007) developed the attentional control theory approach to examine the effect of trait anxiety on cognitive performance. These authors proposed that "*anxiety impairs efficient functioning of the goal-directed attentional system and increases the extent to which processing is influenced by the stimulus-driven attentional system. In addition to decreasing attentional control, anxiety increases attention to threat-related stimuli*" (Eysenck et al., 2007, p. 336). This review article was contemporaneous with Bar-Haim and colleagues' (2007) meta-analysis, where negative attentional bias was observed in anxious individuals compared to non-anxious individuals.

Today, both articles are considered classic references of the direct effect of anxiety on cognitive control.

From the 2010s onwards, empirical articles continued to examine the relation between anxiety and cognitive control using a variety of cognitive paradigms and experimental conditions in both clinical and non-clinical populations. The bulk of the studies on how we regulate emotions still focus on the direct effect of anxiety on cognitive control. Below I will summarize studies that used cognitive experimental techniques and self-report questionnaires to assess this relation, dividing the discussion in the most used cognitive paradigms.

Direct effect of anxiety on cognitive control

Anxiety and cognitive interference towards emotional stimuli

A good starting point to understand the direct effect of anxiety on cognitive control is an extensive meta-analysis conducted by Bar-Haim and colleagues (2007). The researchers analyzed 172 studies, where they concluded that individuals with high symptoms of anxiety tend to display a negative attentional bias, compared to participants with low anxiety. Although according to Cohen's (1988) *d* effect size index = 0.45, the practical importance of the effect was low, it should be noted that cognitive interference towards emotional stimuli occurred consistently, through a variety of experimental conditions. Specifically, cognitive interference towards emotional stimuli refers to the difference in response times between neutral and negative emotional stimuli.

Comparable to Bar-Haim and colleagues' (2007) findings, Becker and collaborators (2001) found that participants diagnosed with generalized anxiety disorder provided slower responses on a modified Stroop task than participants of a control group. Likewise, several authors using the emotional Stroop task have reported that highly anxious participants usually have slower reaction times than subjects in control conditions (Chen et al., 2013). Anxious participants perform poorly on this task because they tend to allocate much of their cognitive resources toward responding to threatening stimuli, which possibly causes a distraction and reduced task scores (Mogg & Bradley, 2005)

Anxiety and reversal learning

In the context of discriminations involving two alternatives, reversal learning is the effect of reversing the contingencies associated with the two alternatives (VandenBos, 2015). For example, participants in a classic reversal learning study were trained to discriminate between two visual stimuli or spatial locations, one of which was associated with a reward, while the other had no reward (Fellows & Farah, 2003). After reaching a criterion level of performance, the contingencies were reversed, so the stimuli that were previously associated with a reward would no longer be associated with a reward, and vice versa. Reversal learning was demonstrated when the participants adapted to the new contingencies. There is a trend in studies using cognitive experiments showing that participants with high trait anxiety tend to have inferior reversal learning scores compared to individuals with low trait anxiety (Browning et al., 2015; Wilson et al., 2018).

In a go/no-go reversal learning task, a participant must learn through practice whether a stimulus is associated with a ‘Go’ response or a ‘No-go’ response. Then contingencies change without notice at some point in the task. For instance, the go/no-go reversal learning task was used in a recent experimental study to examine participants’ anxiety levels and their abilities to flexibly adapt their goal-oriented behaviors in the face of changing environmental challenges (Wilson et al., 2018). Participants with high trait anxiety were found to have smaller scores on measures of reversal learning, in comparison to their counterparts with low trait anxiety. High trait anxiety was associated with a reduced ability to adapt to changing circumstances, when trying to overcome an acquired response.

Similarly to Wilson and colleagues (2018), Browning and coworkers (2015) had previously shown that individuals with higher trait anxiety tend to display less ability to adjust their expectations between stable and changing environments. An aversive learning task was used, where participants with low anxiety performed better than their high anxiety counterparts, in the update of outcome expectations across environments. Contrary to previous studies in adult populations, no differences in reversal learning ability were found in a probabilistic response reversal task between anxious and non-anxious children and adolescents (Dickstein et al., 2010).

Anxiety and task-switching cost

In the context of task-switching studies, switch cost is the loss in efficiency associated with redirecting attention from one task to another (VandenBos, 2015). The first task-switching paradigm was most-likely designed by Jersild (1927), where he demonstrated that subjects have slower reaction times when performing two tasks in rapid succession, compared to performing a single task. However, the popularity of this paradigm increased among cognitive psychologists in the mid-1990s with Roger and Monsell’s (1995) paper. Equally important, there is a trend in studies using task-switching paradigms, where subjects with high trait anxiety have poorer switch cost outcomes compared to participants with low trait anxiety (Ansari et al., 2008; Gul & Humphreys, 2014).

Attentional control theory proposes that anxiety impairs processes required to optimally alternate between tasks (Eysenck et al., 2007). For example, Ansari and coworkers (2008) evaluated the effect of trait anxiety on cognitive control using a mixed antisaccade task. Saccade is a rapid eye movement that allows visual fixation to jump from one location to another in the visual field (VandenBos, 2015). In particular, the task required participants to randomly switch between anti- and prosaccade tasks in the mixed task block, whereas they performed either the antisaccade or the prosaccade task separately in the single task block. After examining the cost of switching between tasks, it was found that people with high trait anxiety did not exhibit the commonly obtained improvement in saccadic latency, compared to individuals with low trait anxiety.

Analogous to Ansari and coworkers (2008), Gul and Humphreys (2014) used an experimental design to examine the effect of anxiety on performance in a computerized switching task. Anxiety was identified as a significant predictor of the cost associated with task switching. Specifically, individuals with high symptoms of anxiety showed difficulties in exercising an efficient cognitive control. In contrast with previous authors, Gustavson and collaborators (2018) demonstrated that the effects of anxiety on cognitive control are limited to situations where the individual must leave aside an effortfully established task set.

The preceding studies combined questionnaire data collection and computerized tasks to examine the effect of trait anxiety on cognitive control. In these studies, it seemed that some cognitive variables may have an effect. Specifically, cognitive flexibility, cognitive avoidance, decentering, and dispositional mindfulness were identified as possible mediators of the association between trait anxiety and cognitive control. Although some authors pointed out the implications of their findings to understand the mechanisms underlying this relation, they did not discuss this issue in detail (Ansari et al., 2008). Similarly, only a small proportion of studies tend to focus on examining the mediating mechanisms of the relation between anxiety and cognitive control. Consequently, relatively little is known about these intermediate variables. Below, I will discuss these variables and how they have been studied in the cognitive literature.

Mediating mechanisms

Cognitive flexibility

Two main research topics were identified in the process of reviewing the literature on the relation between cognitive flexibility and anxiety. Specifically, we focused on reviewing empirical articles that used questionnaires, neuropsychological tests, and computerized tasks as data collection techniques. We observed that some researchers have concentrated on studying the association between anxiety, cognitive flexibility, and cognitive restructuring (Johnco et al., 2014, 2015), while other authors have focused on investigating the relation between cognitive flexibility deficits and anxiety (Kertz et al., 2016; Simon & Verboon, 2016).

Regarding the association between anxiety, cognitive flexibility, and cognitive restructuring, in an experimental study by Johnco and colleagues (2015), participants with generalized anxiety disorders were found to have low levels of cognitive flexibility, resulting in poor learning outcomes in a cognitive restructuring intervention. In a previous study, Johnco and colleagues (2014) found that individuals with low cognitive flexibility were less likely to effectively use cognitive restructuring strategies to alleviate emotional distress.

In terms of the relation between cognitive flexibility deficits and anxiety, Simon and Verboon (2016) used a cross-sectional survey design, where they found a positive correlation between psychological inflexibility and anxiety. An interpretation of the inferential statistical analysis suggests that high cognitive inflexibility scores are associated with higher anxiety symptoms. Like Simon and Verboon, Kertz and coworkers (2016) found that higher levels of anxiety were associated with lower cognitive flexibility scores in a task switching paradigm.

In general, the reviewed studies showed that anxiety has a negative effect on cognitive flexibility as an emotional regulation strategy. This trend is constant in studies that collected data with self-report questionnaires and also in those that used neuropsychological tests, and computerized cognitive tasks. Consequently, this suggests that the influence of anxiety on cognitive flexibility encompasses both participants' perception and objective measures of their performance.

Cognitive avoidance

In a classic paper, de Ruiter and Brosschot (1994) proposed that cognitive avoidance strategies are responsible for the high interference effects displayed by anxious participants in the emotional Stroop task. Cognitive avoidance is a term that represents several strategies, such as distraction, worry, and thought suppression, aimed at avoiding or escaping thoughts about undesirable situations or problems (Sagui-Henson, 2017). Likewise, recent studies continue to examine different aspects of the relation between cognitive avoidance and anxiety. For example, experiential avoidance was found to predict the maintenance of anxiety disorders in a longitudinal cohort study (Spinhoven et al., 2017). Specifically, the authors concluded that the tendency towards experiencing frequent negative emotions and the use of cognitive avoidance strategies are long-term predictors of anxiety disorders.

Furthermore, Williams (2015) conducted a correlational investigation where students with higher intolerance for uncertainty scores were more likely to use cognitive avoidance as a coping strategy. These students also developed greater levels of anxiety toward statistics. Since the author acknowledged that the scope of her study was correlational, she suggested that future studies should analyze the causal aspects of these relations. Equally important, Mahoney and colleagues (2018) demonstrated that maladaptive behaviors exert an indirect effect on anxiety symptoms, through cognitive avoidance strategies.

Decentering

The concept of decentering refers to any variety of techniques aimed at changing one's centered thinking to openminded thinking (VandenBos, 2015). Decentering is considered as a mechanism that exerts beneficial effects on mental health, whereas the absence of this capability is associated with psychological dysfunction (Kessel et al., 2016). For example, a negative relation between measures of decentering and anxiety has been recognized in studies using a variety of cognitive behavioral therapies for reducing anxiety (Hayes-Skelton & Lee, 2018; O'Toole et al., 2019). Therefore, subjects with high decentering abilities tend to obtain lower scores on anxiety measures, and vice versa (Hayes-Skelton & Graham, 2013).

In a recent study, O'Toole and collaborators (2019) found that decentering is a metacognitive strategy that has an inverse relation with worry and anxiety symptoms. These findings suggest that decentering is an adaptive emotional regulation strategy for reducing worry in patients with generalized anxiety disorders. Comparable to O'Toole and collaborators (2019), Hayes-Skelton and Lee (2018) showed that using decentering strategies in cognitive behavioral group therapy is effective in reducing social anxiety. Similarly, Hayes-Skelton and coworkers (2015) conducted a randomized clinical trial where they showed that an increase in self-reported decentering is associated with lower anxiety symptoms. These findings evidenced those decentering strategies as a possible mechanism of action in behavioral therapies based on acceptance and applied relaxation. Interestingly, Hayes-Skelton and Graham (2013) identified that decentering strategies exert a partial mediating role in the relation between dispositional mindfulness and social anxiety. A better understanding of the underlying mechanisms will allow the development of more effective and efficient therapies.

Dispositional mindfulness

Mindfulness, a form of meditation originally developed in the Buddhist traditions of Asia, is a moment-to-moment awareness, based on our inner capacities for relaxation, paying attention, awareness, and insight (Kabat-Zinn, 1990, 1994). A variety of mindfulness-based therapeutic interventions have been developed to help people avoid destructive habits and responses by learning to observe their thoughts and emotions without judging or reacting to them (VandenBos, 2015). Over the years, research has been consistent in identifying a positive association between mindfulness practice and measures of reduced distress, such as anxiety (Boettcher et al., 2014; Kabat-Zinn, 2003; Sunquist et al., 2018). Therefore, the practice of mindfulness is highly regarded as an adaptative emotional regulation strategy.

Equally important, Brown and coworkers (2007) proposed that trait mindfulness, also known as dispositional mindfulness, reflects a greater tendency to abide in mindful states over time. Both, reviews of literature and self-report studies have demonstrated a negative relation between dispositional mindfulness and symptoms of anxiety (Brown & Ryan, 2003; Cernetic, 2015; Rodrigues et al., 2017). Therefore, participants with high levels of dispositional mindfulness tend to score low on measures of anxiety. To understand how this relation occurs, several researchers have focused on examining the direct and indirect effects of dispositional mindfulness on anxiety, through the various cognitive and affective mechanisms that mediate this relation (Freudenthaler et al., 2017; Ostafin et al., 2014; Parmentier et al., 2019).

Summary of findings and research gap

Only a relatively small proportion of studies have focused on analyzing the intermediate variables underlying the relation between anxiety symptoms and cognitive control. A common limitation of these studies is based on the use of the self-report questionnaire as the sole technique of data collection. A disadvantage of this approach is that it mostly focuses on the explicit recollection and analysis of the participant about their recollections and experiences, neglecting how people act in the presence of emotional or potentially anxious information. The use of cognitive tasks makes it possible to evaluate these processes, although in a control and potentially non-ecological context. Because no research techniques allow to delve into all relevant aspects of the relation between cognition and emotion, it is desirable that future studies examine the mechanisms that mediate the relation between anxiety and cognitive control using different data collection techniques. For instance, by combining data from questionnaires and cognitive computerized tasks, it is possible to compare participants' perceptions with their actual performances. Applying these best practices facilitates the process of producing more useful findings to better understand the multidimensionality of these phenomena. Learning about the mediating effects of cognitive flexibility, cognitive avoidance, decentering, and dispositional mindfulness on the relation between anxiety and cognitive control is helpful to design prevention and intervention strategies that promote balanced and adaptive thinking styles.

Research questions

Based on the analysis of the literature above, this study aimed to answer the following research questions:

1. How are trait anxiety and cognitive interference towards emotional stimuli related?

2. How are trait anxiety and reversal learning related?
3. How are trait anxiety and task switching cost related?

Hypotheses

1. Trait anxiety exerts an indirect effect on cognitive interference towards emotional stimuli, through cognitive flexibility and cognitive avoidance.
2. Trait anxiety exerts an indirect effect on reversal learning, through cognitive flexibility, dispositional mindfulness, and decentering.
3. Trait anxiety exerts an indirect effect on task switching cost, through cognitive flexibility, dispositional mindfulness, and decentering.

Research overview

We translated into Spanish and validated five self-report scales originally written in English that measure trait anxiety (State-Trait Anxiety Inventory - Trait, Spielberger et al., 1983), cognitive flexibility (Cognitive Flexibility Inventory, Dennis & Vander-Wal, 2010), cognitive avoidance (Cognitive Avoidance Questionnaire, Sexton & Dugas, 2008), decentering (Experiences Questionnaire, Fresco et al., 2007), and dispositional mindfulness (Mindful Attention Awareness Scale, Brown & Ryan, 2003). Additionally, we designed three cognitive computerized tasks to measure cognitive interference towards emotional stimuli, reversal learning, and task switching cost. We obtained electronic consent from each participant prior to administering the survey and cognitive computerized tasks. Afterwards, 1) the correlation between the measures was studied, and 2) a two-step structural equation modeling approach was used to examine whether there were significant mediation effects of the variables in the relation between anxiety and cognitive control.

Method

Participants and procedure

A non-probability sampling (Henry, 1990) approach was used to recruit 180 Spanish-speaking young adults between the ages of 18-29 years. Participants completed self-report questionnaires and cognitive computerized tasks in approximately one hour. Before collecting the data, the procedure was approved by the Institutional Review Board (IRB: 00000944) of the University of Puerto Rico, Río Piedras Campus (Protocol number: 1920-040).

The study was promoted electronically, mostly through email and social media. We designed an online survey consisting of a consent form, a sociodemographic questionnaire, and other self-report instruments that measure cognitive flexibility, cognitive avoidance, dispositional mindfulness, decentering, and trait anxiety. The three cognitive computerized tasks were designed using E-Prime 3.0 software (Psychology Software Tools, Pittsburgh, PA) and were administered remotely using E-Prime Go 1.0. The computerized tasks measure cognitive interference towards emotional stimuli, reversal learning, and task switching cost, respectively. In addition, each participant received $10.00 as an incentive after completing their participation in the study.

There were 30 participants (16.7%) that experienced technical problems related to the cognitive computerized tasks and, therefore, this data was not saved and excluded from the analyses. Furthermore, we removed one participant that met the criteria to be a multivariate outlier based on the Mahalanobis distance criterion (Kassambara, 2021). Table 1 summarizes the demographic characteristics for the final sample of 149 Spanish-speaking young adults that provided complete data in the tasks (ages 18-28, *M*=21.3, *SD*=2.49; 110 females).

Table 1. *Demographic characteristics of the 149 Spanish-speaking young adults*

Characteristic	*n*	%
Sex		
Female	110	73.8
Male	38	25.5
I prefer not to answer	1	0.7
Employment status		
Employed	52	34.9
Unemployed	97	65.1
Academic status		
Student	139	93.3
Non-student	10	6.7
Country of birth		
Puerto Rico	141	94.6
United States	6	4
Colombia	1	0.7
Spain	1	0.7
Area of residence		
Urban	90	60.4
Rural	59	39.6
Faculty		
Social Sciences	59	42.5
Natural Sciences	37	26.6
Humanities	11	7.9
Business Administration	9	6.5
Education	7	5
School of Communication	8	5.8
Law School	3	2.2
General Studies	2	1.4
Engineering	2	1.4
Architecture	1	0.7

Note. The frequencies for Faculty only sum up to 139 because there were 10 non-students in the sample.

Instruments

Cognitive Flexibility Inventory (CFI)

The CFI (Dennis & Vander-Wal, 2010) has 20 items and measures the cognitive flexibility necessary for individuals to successfully replace maladaptive thoughts with adaptive and balanced thinking styles. The Spanish version of the CFI (Maldonado-Martínez et al., 2019) includes items as "C*onsidero múltiples opciones antes de tomar una decisión*" and "*Es importante tomar en cuenta las situaciones difíciles desde distintos ángulos*". The items are classified on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Higher scores indicate better cognitive flexibility capabilities. The original version of the CFI showed evidence of excellent internal consistency (*Cronbach's Alpha* = .90), while the Spanish version of the CFI demonstrated good internal consistency (*Cronbach's Alpha* = .82). Specifically, we used the control subscale, which showed good internal consistency (CFI-C, *Cronbach's Alpha* = .81). Cognitive flexibility was operationalized as the tendency to perceive difficult situations as controllable.

Cognitive Avoidance Questionnaire (CAQ)

The CAQ (Sexton & Dugas, 2008) has 25 items and measures five cognitive avoidance strategies: thought suppression, thought substitution, distraction, avoidance of threatening stimuli, and transformation of images into thoughts. The Spanish version of the CAQ (Maldonado-Martínez et al., 2019) includes items as "*Tengo pensamientos que intento evitar*" y "*A veces me meto en una actividad para no pensar en ciertas cosas*". The items are classified on a 5-point Likert scale from 1 (not at all typical) to 5 (completely typical). Higher scores represent a more frequent use of cognitive avoidance strategies. The original French version of the CAQ showed evidence of high internal consistency (*Cronbach's Alpha* = .95), while the Spanish version of the CAQ also demonstrated an excellent internal consistency (*Cronbach's Alpha* = .90). Specifically, we used the thought suppression (*Cronbach's Alpha* = .75), thought substitution (*Cronbach's Alpha* = 0.60), and distraction (*Cronbach's Alpha* = .78) subscales. Cognitive avoidance was operationalized as strategies that inhibit the emotional processing of feared stimuli.

Mindful Attention Awareness Scale (MAAS)

The MAAS (Brown & Ryan, 2003) has 15 items and measures a unidimensional construct of dispositional mindfulness. The Spanish version of the MAAS (Maldonado-Martínez et al., 2019) includes items as "*Podría estar sintiendo alguna emoción y no darme cuenta hasta algún tiempo después*" y "*Me enfoco tanto con la meta que quiero alcanzar que pierdo contacto con lo que estoy haciendo ahora mismo para poder alcanzarla*". The items are classified on a 6-point Likert scale from 1 (almost always) to 6 (almost never). Higher scores represent greater levels of dispositional mindfulness. The original version of the MAAS showed evidence of good internal consistency (*Cronbach's Alpha* = .82) and the Spanish version of the MAAS also demonstrated a good internal consistency (*Cronbach's Alpha* = .85). Dispositional mindfulness was operationalized as a trait that reflects a greater tendency to abide in mindful states over time (Brown et al., 2007).

State-Trait Anxiety Inventory - Trait (STAI-T)

The STAI-T (Spielberger et al., 1983) has 20 items and measures trait anxiety. The Spanish version of the STAI-T (Maldonado-Martínez & Tirado-Santiago, 2020) includes items as "*Algunos pensamientos sin importancia rondan por mi mente y me incomodan*" y "*Tomo las decepciones tan intensamente que no puedo sacarlas de mi mente*". The items are classified on a 4-point Likert scale from 0 (not at all) to 3 (very much so). Higher scores represent greater levels of trait anxiety. Previous versions of the STAI-T showed evidence of good (*Cronbach's Alpha* = .86) to excellent (*Cronbach's Alpha* = .95) internal consistency. Similarly, the Spanish version of the STAI-T demonstrated an excellent internal consistency (*Cronbach's Alpha* = .91). Trait anxiety was operationalized as the tendency to experience and report negative emotions, such as fears, worries, and anxiety across many situations (Gidron, 2013).

Experiences Questionnaire (EQ)

The EQ (Fresco et al., 2007) has 20 items and measures decentering and rumination. The Spanish version of the EQ (Maldonado-Martínez & Tirado-Santiago, 2020) includes items as "*Puedo separarme de mis pensamientos y sentimientos*" y "*Veo las cosas desde una perspectiva más amplia*". The items are classified on a 5-point Likert scale from 1 (never) to 5 (all the time). Higher scores on the decentering subscale represent greater abilities to maintain a broad perspective of thoughts, feelings, and sensations. In contrast, the rumination subscale was developed to control for response bias. Previous versions of the EQ showed evidence of acceptable (*Cronbach's Alpha* = .70) to good (*Cronbach's Alpha* = .83) internal consistency. Likewise, the Spanish version of the EQ showed an acceptable internal consistency (*Cronbach's Alpha* = .68). Decentering was operationalized as any variety of techniques aimed at changing one's centered thinking to openminded thinking (VandenBos, 2015).

Cognitive computerized tasks

Three cognitive computerized tasks were used to measure participants' performance in different aspects of cognitive control. First, the emotional counting Stroop task was used to examine *cognitive interference towards emotional stimuli*. Second, the task-switching alternating paradigm was used to analyze *task switching cost*. Third, the go/no-go reversal learning task was used to assess *reversal learning*.

Emotional counting Stroop

The emotional counting Stroop task was designed using E-Prime 3.0 software (Psychology Software Tools, Pittsburgh, PA), through adapting the cognitive experiment developed by Whalen and collaborators (2006). In addition, we evaluated the dimensions of valence and arousal, as suggested by Redondo and coworkers (2007) to distinguish between 70 neutral and 70 negative emotional words. Specifically, the negative emotional words have low valence and high arousal, while neutral words have intermediate levels of valence and arousal. Of equal importance, both categories of words were matched by an objective index of the number of syllables. Moreover, these words were culturally adapted to the Puerto Rican context. The task instructions are as follows:

> Presiona '1' si ves 1 palabra en la pantalla. Presiona '2' si ves 2 palabras en la pantalla. Presiona '3' si ves 3 palabras en la pantalla. Presiona '4' si ves 4 palabras en la pantalla. ¡Intenta responder rápido, pero sin cometer errores!

The task began with a practice block of 12 stimuli, where feedback was provided on the percent of correct responses. The practice exercises were repeated until the participant scored better than 80 percent. The second block consisted of responding to 140 experimental stimuli with a brief 30 s rest after completing half of these stimuli. No feedback was provided to the participant during the experimental block. Cognitive interference towards emotional stimuli was operationalized as the difference in reaction times between neutral and negative emotional words. The sequence of events in the emotional counting Stroop task is illustrated in Figure 1.

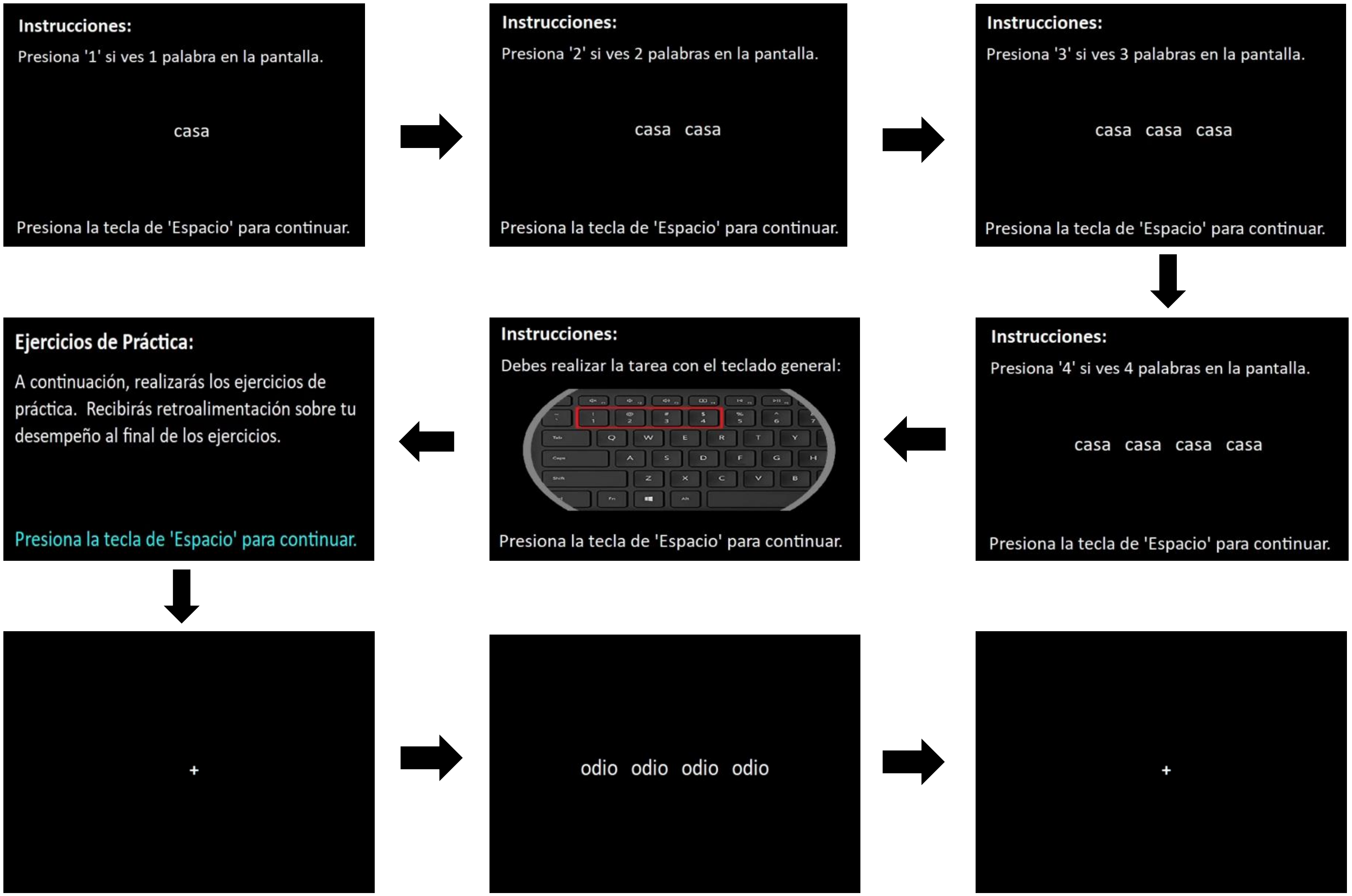

Figure 1. *Sequence of events in the emotional counting Stroop task (adapted from Whalen et al., 2016). We evaluated the dimensions of valence and arousal, as suggested by Redondo and coworkers (2007) to compare participant's reaction times to 70 neutral and 70 negative emotional words, which were matched by an objective index of the number of syllables. A fixation symbol (+) with a duration of 500 ms preceded each stimulus.*

Task-switching alternating

The task-switching alternating paradigm was designed using E-Prime 3.0 software (Psychology Software Tools, Pittsburgh, PA), based on Rogers and Monsell (1995) classic study. A combination of letter and number was displayed on the computer screen, for example: G1. On the one hand, if the letter/number combination appeared at the top of the screen, the participant had to attend to the letter. The participant had to press the letter ‘n’ if the letter was consonant or the letter ‘b’ if the letter was vowel. On the other hand, if the letter/number combination appeared at the bottom of the screen, the participant had to attend to the number. The participant had to press the letter ‘n’ if the number was odd or the letter ‘b’ if the number was even.

The first block of the task consisted of responding to 10 practice stimuli and 40 experimental stimuli, where the participant only had to attend to the letters. The second block of the task consisted of responding to 10 practice stimuli and 40 experimental stimuli, where the participant only had to attend to the numbers. The third block of the task consisted of responding to 20 practice stimuli and 80 experimental stimuli, where the participant had to attend to a mixed condition of letters or numbers.

The response pattern in the mixed condition was predictable. For example, after responding to two successive letter stimuli (task repeat condition), the participant always had to respond to the number in the next stimulus (task switching condition). The task switching cost was operationalized as the difference in reaction times between the task switching and task repeat conditions. The sequence of events in the task-switching alternating paradigm is illustrated in Figure 2.

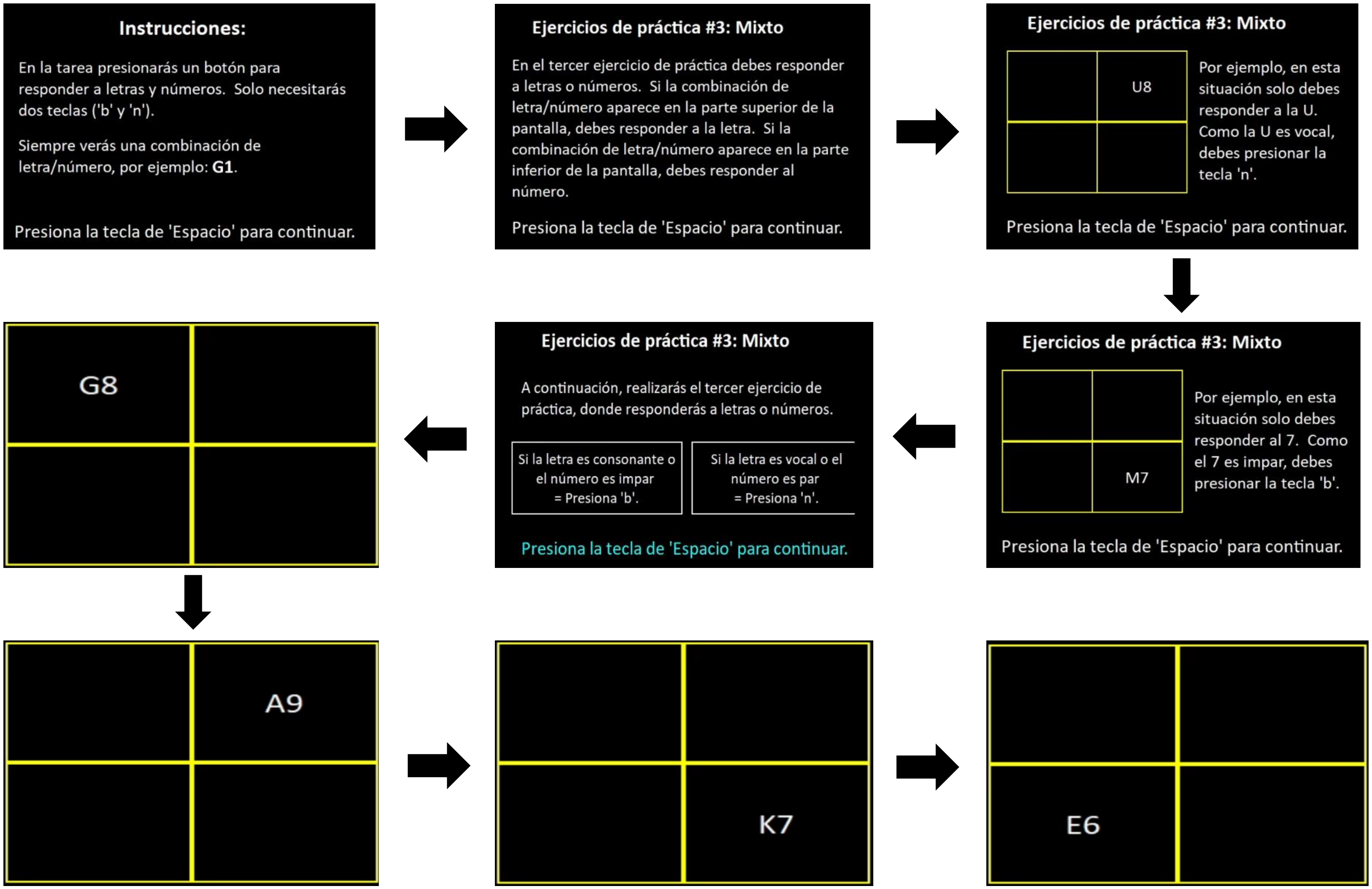

Figure 2. *Sequence of events in the task-switching alternating task (Roger & Monsell, 1995). The stimulus location rotated in a predictable clockwise direction on every trial, with the task switching when the stimulus crossed the horizontal mid-section. Therefore, performance in the upper-left and the lower-right squares reflect task switch trials, whereas performance on the upper-right and lower-left squares reflect task repeat trials.*

Go/no-go reversal learning

The go/no-go reversal learning task was designed using E-Prime 3.0 software (Psychology Software Tools, Pittsburgh, PA), through modifying the cognitive experiment developed by Wilson and coworkers (2018). Multiple images were displayed on the computer screen, one at a time. Specifically, there were two categories of images consisting of 7 polygonal stimuli and 7 non-polygonal stimuli. A polygon is the union of three or more lines segments that are joined end to end so as to completely enclose an area (Downing, 2009). The participant had to press the ‘Space’ key when observing the polygon images (e.g., a rectangle), but not on others (e.g., a cloud). The stimuli in which the participant had to press the ‘Space’ key were called ‘Go’, while the other stimuli were called ‘No-go’. The participant had to learn through practice whether the image was associated with a ‘Go’ response or a ‘No-go’ response.

Contingencies changed without notice upon completion of approximately two-thirds of the stimuli. Therefore, images that were previously associated with a ‘Go’ response became associated with a ‘No-go’ response, and vice versa. Specifically, the task consisted of 63 stimuli: 1) the first 42 stimuli represented the learning phase, 2) the next 7 stimuli represented the reversal phase, and 3) the last 14 stimuli represented the recovery phase. The participants received feedback on each stimulus, indicating whether they gave a correct or incorrect response. Reversal learning was operationalized as the ability to improve discrimination of ‘go/no-go’ stimuli during the recovery phase. The sequence of events in the go/no-go reversal learning task is illustrated in Figure 3.

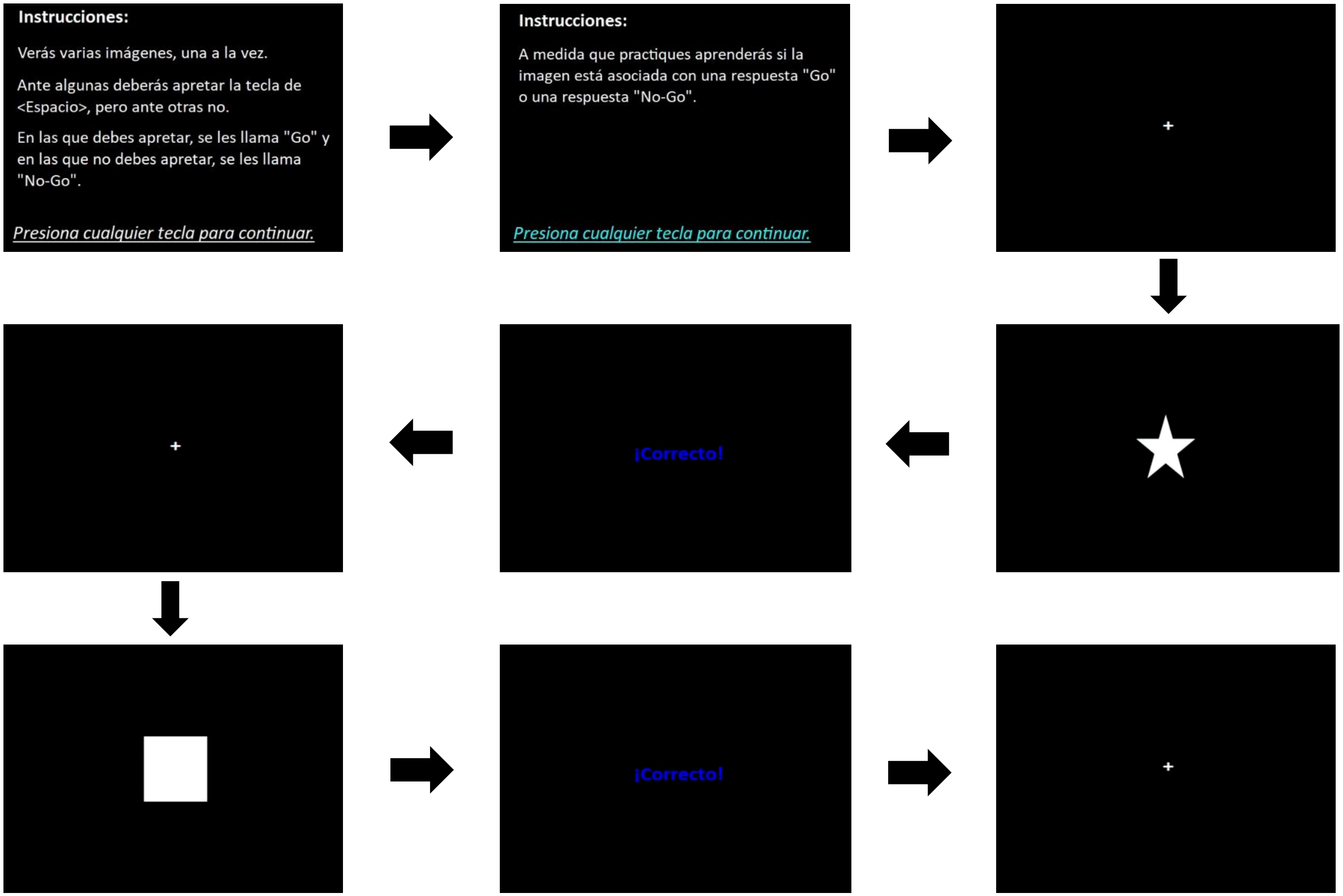

Figure 3. *Sequence of events in the Go/no-go reversal learning task (adapted from Wilson et al., 2018). The participants had to learn through practice whether each image was associated with a 'Go' or a 'No-go' response. The participants received feedback on each stimulus, indicating whether they gave a correct or incorrect response. Contingencies changed without notice upon completion of approximately two-thirds of the stimuli. A fixation symbol (+) with a duration of 500 ms preceded each stimulus.*

Statistical analysis approach

The statistical analyses were conducted using R statistical software (R Core Team, 2020). We used the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011) and the *md.pattern* function to perform a preliminary analysis of the missing values. Afterwards, we used the *BaylorEdPsych* package (Beaujean, 2012) and the *LittleMCAR* function to assess whether the missing values met the missing completely at random (MCAR) criteria. Evaluating the MCAR assumption is useful for informing the methods that will be used to address missing values (Appelbaum et al., 2018). Although, the missing values met the MCAR assumption, we used the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011) multiple imputation method with predictive mean matching to address missing data, rather than using less robust methods such as mean substitution (Kleinke, 2017).

Subsequently, we examined the distributional assumption of multivariate normality using several statistical diagnostic functions. First, we used the *rstatix* package (Kassambara, 2021) and the *mahalanobis_distance* function since the Mahalanobis distance is a common metric used to identify multivariate outliers (Field, 2017). The larger the value of Mahalanobis distance, the more unusual the data point and the more likely it is to be a multivariate outlier (Kassambara, 2021). Second, we used the *semTools* package (Jorgensen et al., 2021) and the *skew and kurtosis* functions since the skew and kurtosis measures are useful for performing a numeric analysis of the distribution of the data. These measures were used to perform a numeric assessment of the univariate and multivariate normality assumptions (Field, 2017). Third, we used the *ggpubr* package (Kassambara, 2020) and the *ggqqplot* function since the QQ-plots are useful for performing a visual analysis of the distribution of the data. These plots were used to perform a visual assessment of the univariate normality assumption (Field, 2017). Fourth, we used the

RVAideMemoire package (Hervé, 2021) and the *mqqnorm* function to perform a visual assessment of the multivariate normality assumption. The multivariate QQ-plot was used to perform a visual assessment of the multivariate normality assumption. Fifth, we used the *ggplot2* package (Wickham, 2016) and the *ggplot* function to visualize the data and analyses. The scatterplots are useful for visually examining the association between two variables. These plots were used to perform a visual analysis of the linearity assumption between each pair of variables (Kline, 2016).

After confirming that the data did not meet the univariate and multivariate normality assumptions, we examined the Kendall's correlations between each pair of variables. We did not use the traditional Pearson correlation because it is advisable to use non-parametric correlation techniques when using data with non-normal distributions (Field, 2017). Then, we used the correlogram as a complementary visual aid to understand the patterns of relations in the Kendall's correlation matrix (Kassambara, 2021).

Next, we examined the personality characteristics of the sample using various statistical analyses. First, we computed the terciles to identify the range of values of the personality characteristics. Second, we used several ANOVAs to examine between-group differences by anxiety level (low, medium, or high), sex (male or female), and employment status (employed or unemployed). Third, we used the Kruskal-Walli's test to examine whether the ANOVAs main effects (e.g., anxiety with three levels) were still significant when removing the other main effects, and two- and three-way interactions. Fourth, we used the Wilcoxon rank-sum test to examine whether the ANOVAs main effects (e.g., anxiety with two levels, sex, and employment status) were still significant when removing the other main effects, and two- and three-way interactions. The violin plots with boxplots were used to illustrate the between-group differences in the personality characteristics by anxiety level, sex, and employment status. We conducted these analyses using both the main sample and a subsample of *N*=98 participants with extreme anxiety (low or high) scores.

Afterwards, we used the Wilcoxon signed-rank test to examine whether there were within-subject differences across each of the cognitive computerized task's conditions or times. A significant 'within-subjects' difference in this analysis shows empirical evidence of the validity of each task, and vice versa. Then, we examined the performance of the sample in the cognitive computerized tasks using the same set of statistical techniques previously employed to assess the personality characteristics, both in the main sample and a subsample of *N*=98 participants with extreme anxiety (low or high) levels.

We applied established item-parceling procedures (e.g., Houghton & Jinkerson, 2007) in the current study. Specifically, the following sets of items were randomly divided and summed to form three composite indicator variables of cognitive flexibility, dispositional mindfulness, decentering, and trait anxiety, respectively: CFI (control subscale [2, 4, 7, 9, 11, 15, 17]); MAAS (1 through 15); EQ (decentering subscale [3, 6, 9, 10, 12, 14, 15, 16, 17, 18, 20]); STAI-T (1 through 20). Likewise, we formed three composite indicators of cognitive avoidance based on the sum of the following subscales: CAQ (thought suppression subscale [1, 2, 5, 6, 14], thought substitution subscale [4, 11, 17, 20, 25], and distraction subscale [8, 10, 12, 13, 21]). These composite indicators were treated as reflective continuous variables in the measurement model. Descriptive statistics and Pearson correlations among variables are presented in Table 6.

Furthermore, we used the *lavaan* package (Rosseel, 2012) and the *sem* function to perform a parallel mediation analysis. The objective of parallel mediation analysis is to establish the degree to which a causal variable, X, influences a criterion variable, Y, through various mediating variables (Hayes, 2018). This analysis allows to examine both the direct and indirect effects of trait anxiety on task-switching cost and reversal learning. A two-step structural equation modeling (SEM) approach was used. Two-step structural equation modeling is a broad class of statistical models consisting of two parts: the measurement model and the structural model. In the measurement model, the latent variables are defined, based on the observed variables. In the structural model, regression analyses are performed between the latent variables. When examining structural equation models, it is necessary to establish that the measurement model is consistent with the data before analyzing the relations between latent variables and, thus, model re-specifications were planned a priori if the original model were to be rejected. The final sample size (N=149) was only one participant below the recommended rule of thumb (N=150) by Hair and others (2014) in structural equation models that include seven constructs or less and, therefore, it is considered acceptable.

We reported the Chi-Square test, comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), as suggested by Kline (2016) to evaluate the global fit of SEM models. We used Hu and Bentler's (1999) guidelines to evaluate acceptable threshold levels for each fit index: 1) CFI of 0.95 or greater, 2) RMSEA of 0.06 or lower, and 3) SRMR of 0.08 or lower. We used maximum likelihood estimation with robust standard errors and Satorra and Bentler's (2001) adjusted fit indices considering the non-normality of the data. The unstandardized and standardized parameter estimates of the direct and indirect effects with robust standard errors were used to interpret the results. We inspected the local fit (e.g., correlation residuals) of the various measurement and structural models and computed a post hoc power analysis of the retained partially latent parallel mediation model. An overview of the statistical analysis approach is presented in Table 2.

Table 2. *Overview of the statistical analysis approach*

Statistical analysis	Description	R package	Rationale
Little's test	The Little's test evaluates whether the missing values met the missing completely at random (MCAR) assumption.	*BaylorEdPsych* (Beaujean, 2012)	Evaluating the MCAR assumption is useful in informing the methods that will be used to address missing values (Appelbaum et al., 2018).
Multiple imputation	Multiple imputation with predictive mean matching for missing data is a best practice approach for handling missing data in multivariate analyses.	*mice* (van Buuren & Groothuis-Oudshoorn, 2011)	Although the missing values met the MCAR assumption, the multiple imputation method with predictive mean matching was used to address the missing values, rather than using less robust traditional methods such as mean substitution (Kleinke, 2017).
Mahalanobis distance	The Mahalanobis distance is a common metric used to identify multivariate outliers (Field, 2017).	*rstatix* (Kassambara, 2021)	The larger the value of Mahalanobis distance, the more unusual the data point and the more likely it is to be a multivariate outlier (Kassambara, 2021).
QQ-plots	The QQ-plots are useful for performing a visual analysis of the distribution of the data.	*RVAideMemoire* (Hervé, 2021) and *ggpubr* (Kassambara, 2020)	The QQ-plots were used to perform a visual assessment of the univariate and multivariate normality assumptions (Field, 2017).
Skew and kurtosis	The skew and kurtosis measures are useful for performing a numeric analysis of the distribution of the data.	*semTools* (Jorgensen et al., 2021)	The skew and kurtosis measures were used to perform a numeric assessment of the univariate and multivariate normality assumptions (Field, 2017).
Scatterplots	Scatterplots are useful for visually examining the association between two variables.	*ggplot2* (Wickham, 2016)	The scatterplots were used to perform a visual assessment of the linearity assumption between each pair of variables (Kline, 2016).

Statistical analysis	Description	R package	Rationale
Kendall's correlation	Kendall's correlation is a non-parametric correlation coefficient similar to Spearman's correlation coefficient but should be used in preference for a small data set with many tied ranks.	*psych* (Revelle, 2018)	It is advisable to use non-parametric correlation techniques when the data do not meet the normal distribution assumption (Field, 2017).
Correlogram	The correlogram is useful for visualizing the patterns of relations between variables in a correlation matrix.	*rstatix* (Kassambara, 2021)	The correlogram was used as a complementary visual aid to understand the patterns of relations in the Kendall's correlation matrix (Kassambara, 2021).
ANOVA	Analysis of variance (ANOVA) is a statistical procedure used to examine whether there are differences between the means of two or more independent groups (Field, 2017).	*rstatix* (Kassambara, 2021)	Several ANOVAs were used to examine between-group differences by anxiety level, sex, and employment status.
Kruskal-Wallis	Kruskal-Wallis is a non-parametric test equivalent to the one-way ANOVA. Therefore, it is used to examine whether there are differences between two or more independent groups (Field, 2017).	*rstatix* (Kassambara, 2021)	The Kruskal-Wallis test was used to examine whether the ANOVAs main effects remain significant when removing the other main effects, and two- and three-way interactions.
Wilcoxon rank-sum test	Wilcoxon rank-sum-test is a non-parametric test equivalent to the independent samples t-test. Thus, it is used to examine whether there are differences between two independent groups (Field, 2017).	*rstatix* (Kassambara, 2021)	The Wilcoxon rank-sum test was used to examine whether the ANOVAs main effects remain significant when removing the other main effects, and two- and three-way interactions.

Statistical analysis	Description	R package	Rationale
Wilcoxon-signed rank test	Wilcoxon signed-rank test is a non-parametric test equivalent to the paired-samples t-test. Consequently, it is used to examine whether there are within-subject differences across two conditions or times (Field, 2017).	*rstatix* (Kassambara, 2021)	The Wilcoxon signed-rank test was used to examine whether there were within-subject differences across each of the cognitive computerized task's conditions or times.
Violin plots with boxplots	The violin plots with boxplots displays the five-number summary of a set of data (e.g., minimum, first quartile, median, third quartile, and maximum) and shows the Kernel probability density of the data at different values (Kassambara, 2021).	*ggpubr* (Kassambara, 2020)	The violin plots with boxplots were used to illustrate the between-group differences in the personality characteristics by anxiety level, sex, and employment status.
Parallel mediation analysis	The objective of parallel mediation analysis is to establish the degree to which a causal variable, X, influences a criterion variable, Y, through various mediating variables (Hayes, 2018).	*lavaan* (Rosseel, 2012)	The parallel mediation analysis allows to examine both the direct and indirect effects of trait anxiety on task-switching cost and reversal learning.
Two-step structural equation modelling	Two-step structural equation modeling is a broad class of statistical models consisting of two parts: the measurement model and the structural model. In the measurement model, the latent variables are defined, based on the observed variables. In the structural model, regression analyses are performed between the latent variables.	*lavaan* (Rosseel, 2012)	When examining structural equation models, it is necessary to establish that the measurement model is consistent with the data before analyzing the relations between latent variables. Therefore, it is advisable to use a two-step modeling approach, rather than using one-step modeling (Kline, 2016).

Results

Missing data and multiple imputation

Upon initial exploration of the data (*N*=180), we excluded 30 participants (16.7%) that experienced technical problems related to the cognitive computerized tasks and, therefore, their data was not saved. Among the remaining 150 participants, 128 (85.3%) had complete data, 21 (14%) had missing values on one or two variables, and 1 (0.7%) had missing values on three variables. Equally important, all variables had less than 2% of missing values. The Little's test demonstrated that the missing values met the MCAR assumption, $p > .05$. We performed twenty multiple imputations with predictive mean matching and randomly selected the second imputation as the complete dataset. No auxiliary variables were used during data imputation.

Assessing multivariate normality

We performed preliminary statistical diagnostic analyses to examine whether the study variables met the multivariate normality assumption.

Identify multivariate outliers

We identified one participant (Id #20) that met the criteria to be a multivariate outlier, Mahalanobis distance = 27.2. This participant demonstrated an irregular pattern of responses showing a high dispositional mindfulness but also the lowest decentering score among all participants. Similarly, the participant identified herself as a graduate student, while being only 20 years old. We removed this participant from further analyses. Thus, the final sample consisted of 149 Spanish-speaking young adults.

Evaluate univariate and multivariate normality numerically

The skew and kurtosis measures for evaluating univariate and multivariate normality numerically are presented in Table 3. The skew and kurtosis measures for assessing univariate normality suggest that the shape of the distribution of cognitive flexibility, dispositional mindfulness, cognitive avoidance, decentering, and trait anxiety may not be severely non-normal. However, the switch cost, cognitive interference, and reversal learning variables had severely non-normal distributions. Equally important, the Mardia's multivariate skewness of multiple variables indicated a lack of multivariate normality (Mardia, 1970).

Table 3. *Test of skewness and kurtosis measures for evaluating the univariate and multivariate normality assumptions and their respective standard error (se).*

	Skew	*se*	*Z*	*p*	*Kurtosis*	*se*	*Z*	*p*
Cognitive flexibility	-0.240	0.20	-1.20	.23	-0.596	0.40	-1.48	0.14
Dispositional mindfulness	-0.103	0.20	-0.51	.61	-0.571	0.40	-1.42	0.15
Cognitive avoidance	-0.302	0.20	-1.51	.13	-0.615	0.40	-1.53	0.13
Decentering	-0.361	0.20	-1.80	.07	0.179	0.40	0.45	0.66
Trait anxiety	0.002	0.20	0.01	.99	-0.607	0.40	-1.51	0.13
Switch cost	**0.663**	0.20	3.31	<.001	**1.281**	0.40	3.19	0.001
Cognitive interference	**0.413**	0.20	2.06	0.04	**2.044**	0.40	5.09	<.001
Reversal learning	**0.736**	0.20	3.67	<.001	**1.652**	0.40	4.12	< .001

Note. Mardia's multivariate skewness of multiple variables, 6.18, $\chi 2$ (120) = 153.39, $p = 0.02$. Mardia's multivariate kurtosis of multiple variables, 82.23, $z = 1.07$, $p = 0.28$. Estimates in boldface represent a significant departure from normality at the p<.05 alpha level.

Evaluate univariate normality visually

The QQ-plots for evaluating univariate normality visually are presented in Figure 4. The QQ-plots suggest even more distributional problems compared with the skewness and kurtosis estimates. A visual analysis of these graphs seems to indicate that only the distributions of trait anxiety and dispositional mindfulness may not be severely non-normal. However, the other variables showed severely non-normal distributions.

Evaluate multivariate normality visually

The QQ-plot for evaluating multivariate normality visually is presented in Figure 5. A visual inspection of the QQ-plot suggest that the data did not meet the multivariate normality assumption.

Evaluate the linearity assumption

The bivariate scatterplots for evaluating the linearity assumption are presented in Figure 6. A visual inspection of the scatterplots suggest that the data met the linearity assumption for all bivariate relations between variables.

Is the data multivariate normal?

After performing the preliminary statistical diagnostic analyses, we concluded that the study variables did not meet the multivariate normality assumption. However, there were no remaining multivariate outliers in the dataset and the relations between variables were linear.

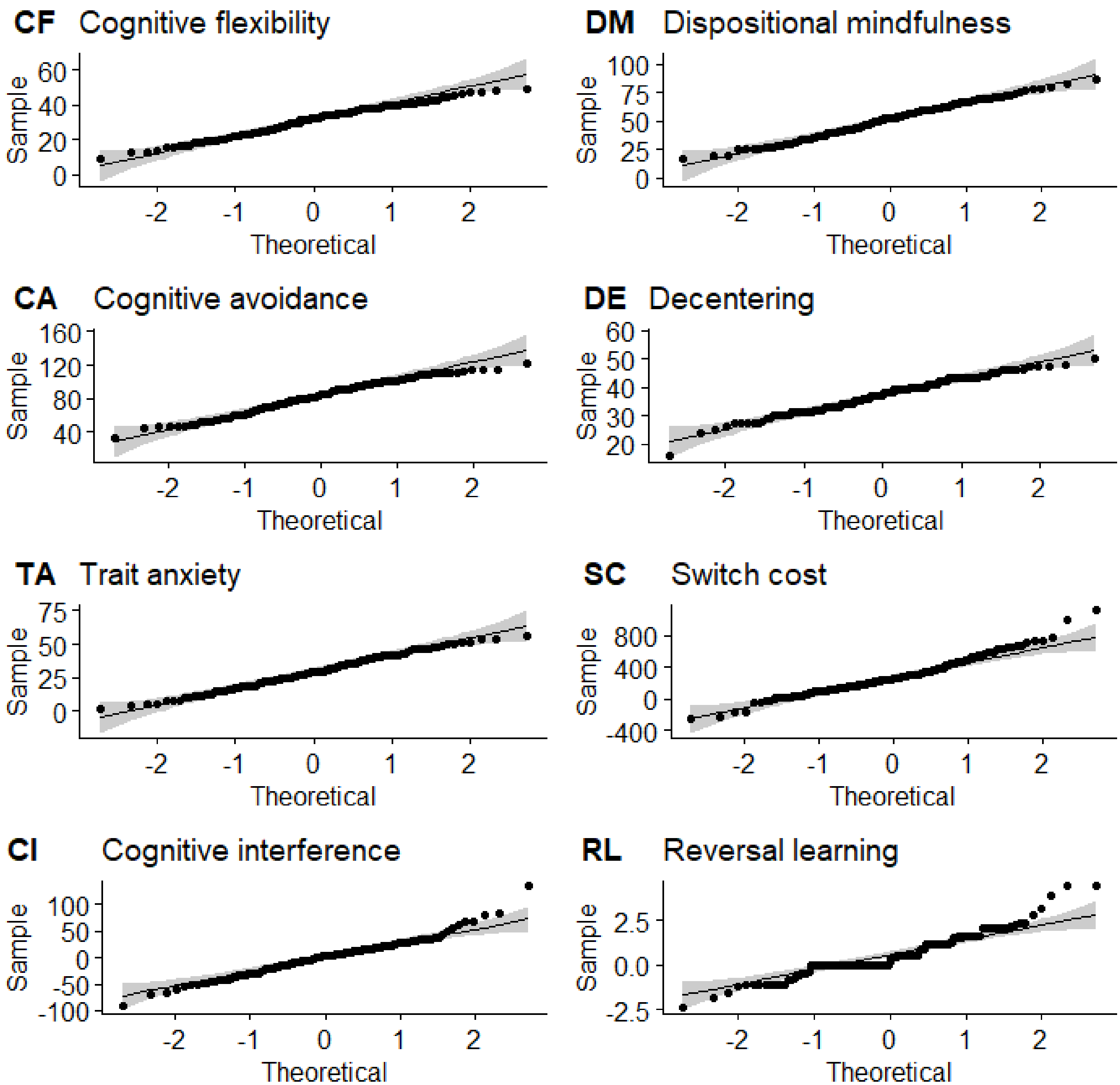

Figure 4. *QQ-plots for evaluating the univariate normality assumption*

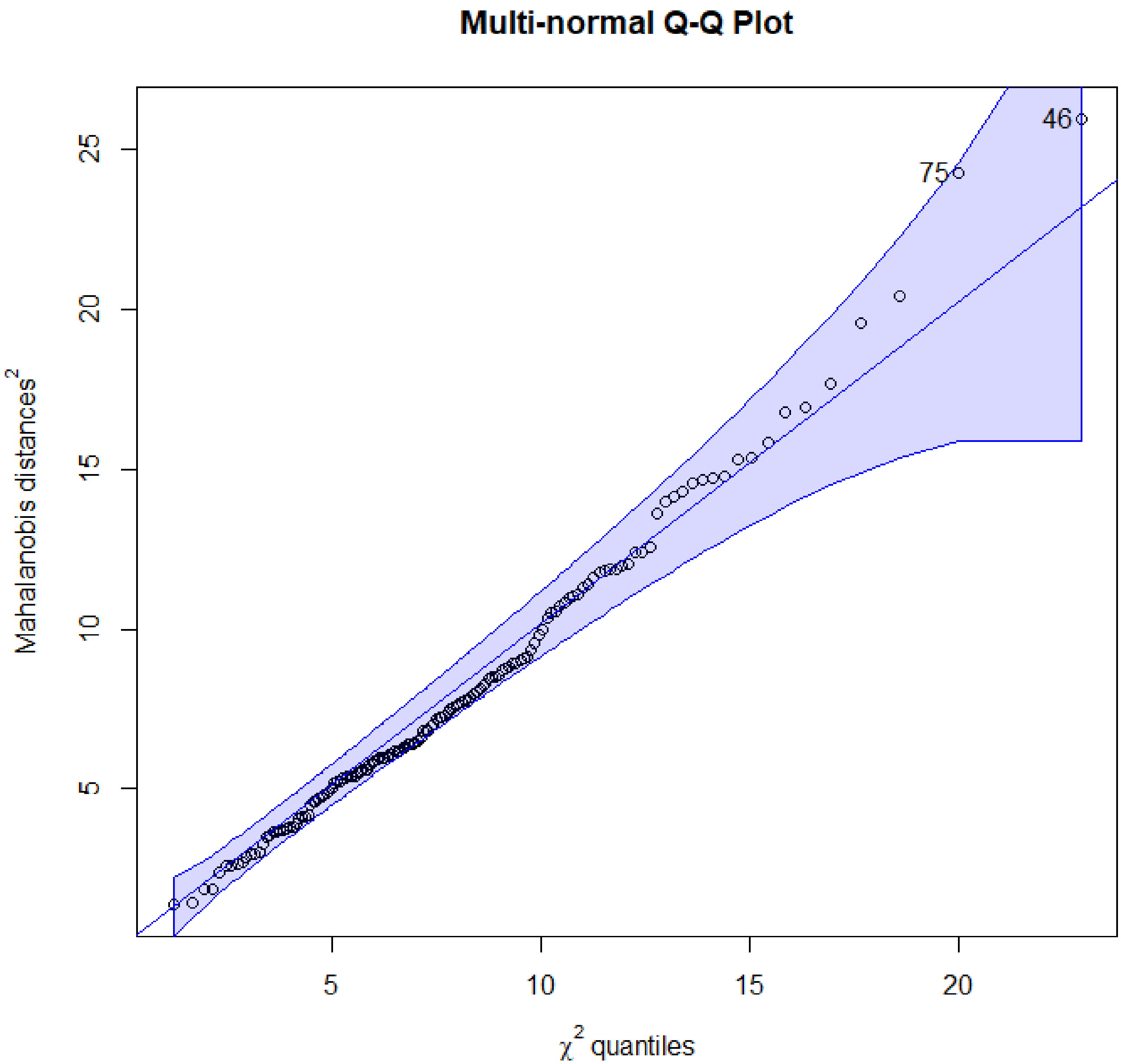

Figure 5. *QQ-plot for evaluating the multivariate normality assumption*

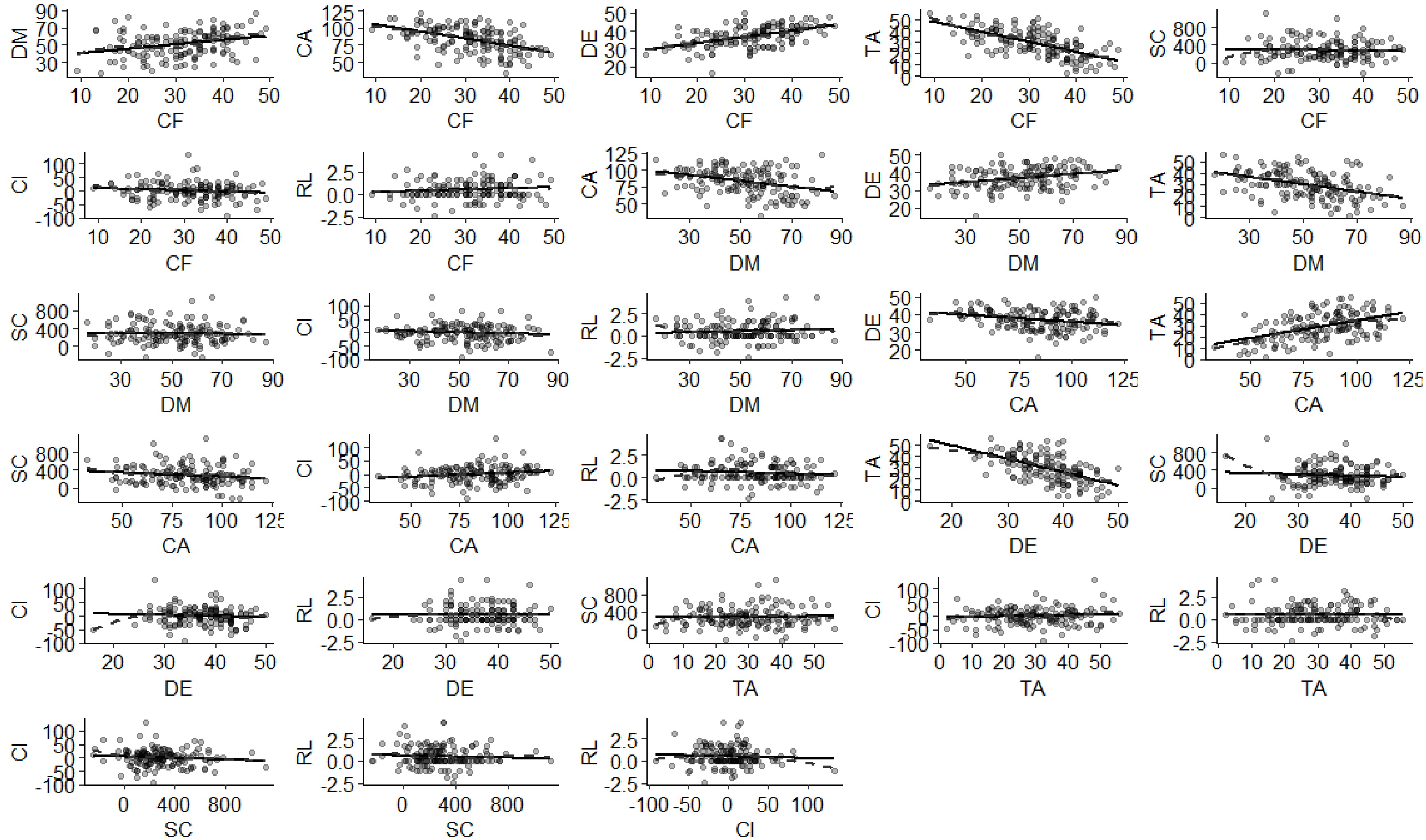

Figure 6. *Scatterplots for evaluating the linearity assumption. CF=Cognitive flexibility; DM=Dispositional mindfulness; CA=Cognitive avoidance; DE=Decentering; TA=Trait anxiety; SC=Switch cost; CI=Cognitive interference; RL=Reversal learning. The solid lines represent linear regressions, while the dashed lines represent loess (locally estimated scatterplot smoothing) non-parametric regressions.*

Medians, interquartile ranges, and Kendall's correlations

The medians, interquartile ranges, and Kendall's correlations among variables are presented in Table 4. Next, we used a correlogram to illustrate the patterns of relations in the Kendall's correlation matrix (see Figure 7).

Table 4. *Medians, interquartile ranges, and Kendall's correlations among variables*

Variable	*Mdn*	*IQR*	1	2	3	4	5	6	7
1. Cognitive flexibility	32	[25, 38]	—						
2. Cognitive avoidance	85	[70, 97]	-.33	—					
3. Dispositional mindfulness	53	[41, 61]	.21	-.23	—				
4. Trait anxiety	29	[21, 38]	-.46	.32	-.29	—			
5. Decentering	37	[33, 41]	.38	-.17	.20	-.42	—		
6. Cognitive interference	2.28	[-17.6, 18.1]	-.06	.11	-.05	.01	-.06	—	
7. Switch cost	257	[139, 396]	0	-.10	-.04	-.01	-.03	-.07	—
8. Reversal learning	0.13	[0, 1.12]	.05	-.07	.04	.05	-.02	-.04	-.03

Note. *Mdn* and *IQR* are used to represent median and interquartile range, respectively.

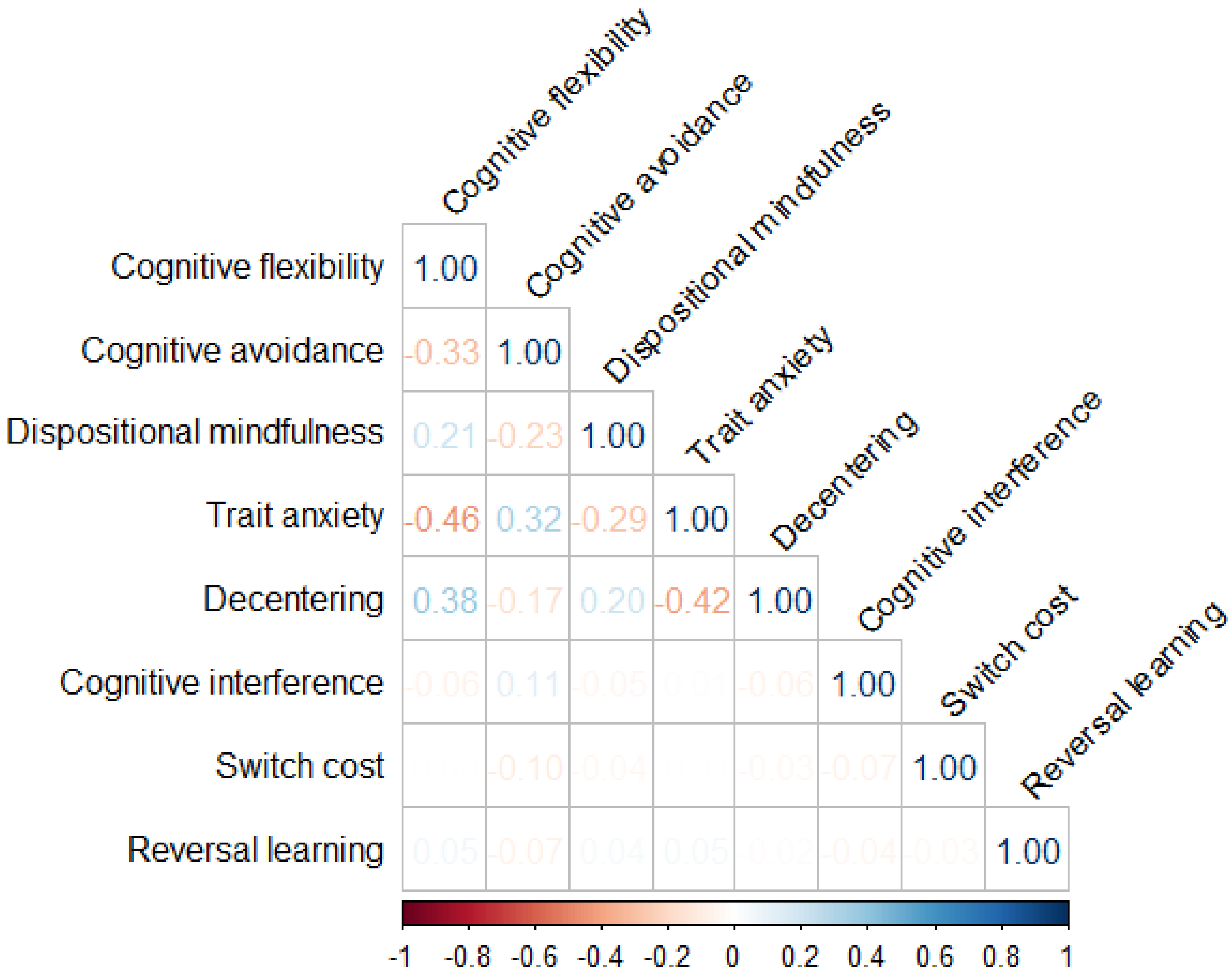

Figure 7. *Correlogram to illustrate the patterns of relations in the Kendall's correlation matrix. Blue and red colors represent positive and negative relations, respectively. The darker the color, the stronger the association.*

Personality characteristics in the main sample

We computed the terciles to identify the range of values of the personality characteristics in the main sample (See Table 5).

Table 5. *Range of values for the personality characteristics in the main sample (N=149)*

Personality characteristic	Range of values	Number of participants
Cognitive flexibility		
Low	9-28	54 (36.2%)
Medium	29-35	47 (31.6%)
High	36-49	48 (32.2%)
Cognitive avoidance		
Low	33-75	50 (33.6%)
Medium	76-93	51 (34.2%)
High	94-122	48 (32.2%)
Dispositional mindfulness		
Low	17-44	52 (34.9%)
Medium	45-59	53 (35.6%)
High	60-87	44 (29.5%)
Trait anxiety		
Low	2-23	50 (33.6%)
Medium	24-35	50 (33.6%)
High	36-56	49 (32.8%)
Decentering		
Low	16-34	53 (35.6%)
Medium	35-40	53 (35.6%)
High	41-50	43 (28.8%)

Next, we examined between-group differences in the personality characteristics (e.g., cognitive flexibility, cognitive avoidance, decentering, and dispositional mindfulness) by anxiety level (low, medium, or high), sex (male or female), and employment status (employed or unemployed). One participant who preferred not to answer the question about his/her sex was excluded from these analyses (N=148).

Cognitive flexibility

We used a three-way ANOVA test, which demonstrated significant main effects of anxiety level, $F(2, 136)=28.25$, $p<.001$ and sex, $F(1, 136)=6.13$, $p=.015$ on cognitive flexibility. However, none of the other main effects or interactions were significant, $p>.05$. Furthermore, we used the Kruskal-Wallis test, which showed a significant main effect of anxiety level on cognitive flexibility when examined independently, $\chi 2(2)=43.90$, $p<.001$ (see Figure 8). We performed pairwise comparisons using the Wilcoxon rank-sum test with the Bonferroni correction and found significant differences between all groups . Specifically, 1) the magnitude of the difference between participants with low (Mdn=38, IQR=7) and medium (Mdn=32.5, IQR=11.2) anxiety was small, W=1,423, $p=.01$, $r=.29$, 2) the magnitude of the difference between participants with low and high (Mdn=24, IQR=11.2) anxiety was large, W=2,084, $p<.001$, $r=.64$, and 3) the magnitude of the difference between participants with medium and high anxiety was moderate, W=1,798, $p<.001$, $r=.43$. The trend of the data shows that the higher the anxiety level, the lower the cognitive flexibility.

Moreover, we used the Wilcoxon rank-sum test, which demonstrated a significant main effect of sex on cognitive flexibility when examined independently, W=1,623, $p=.04$ (see Figure 9). In particular, the male participants (Mdn=34, IQR=8) had higher cognitive flexibility levels compared to their female counterparts (Mdn=31, IQR=14). However, the effect size had a small practical importance, $r=.17$.

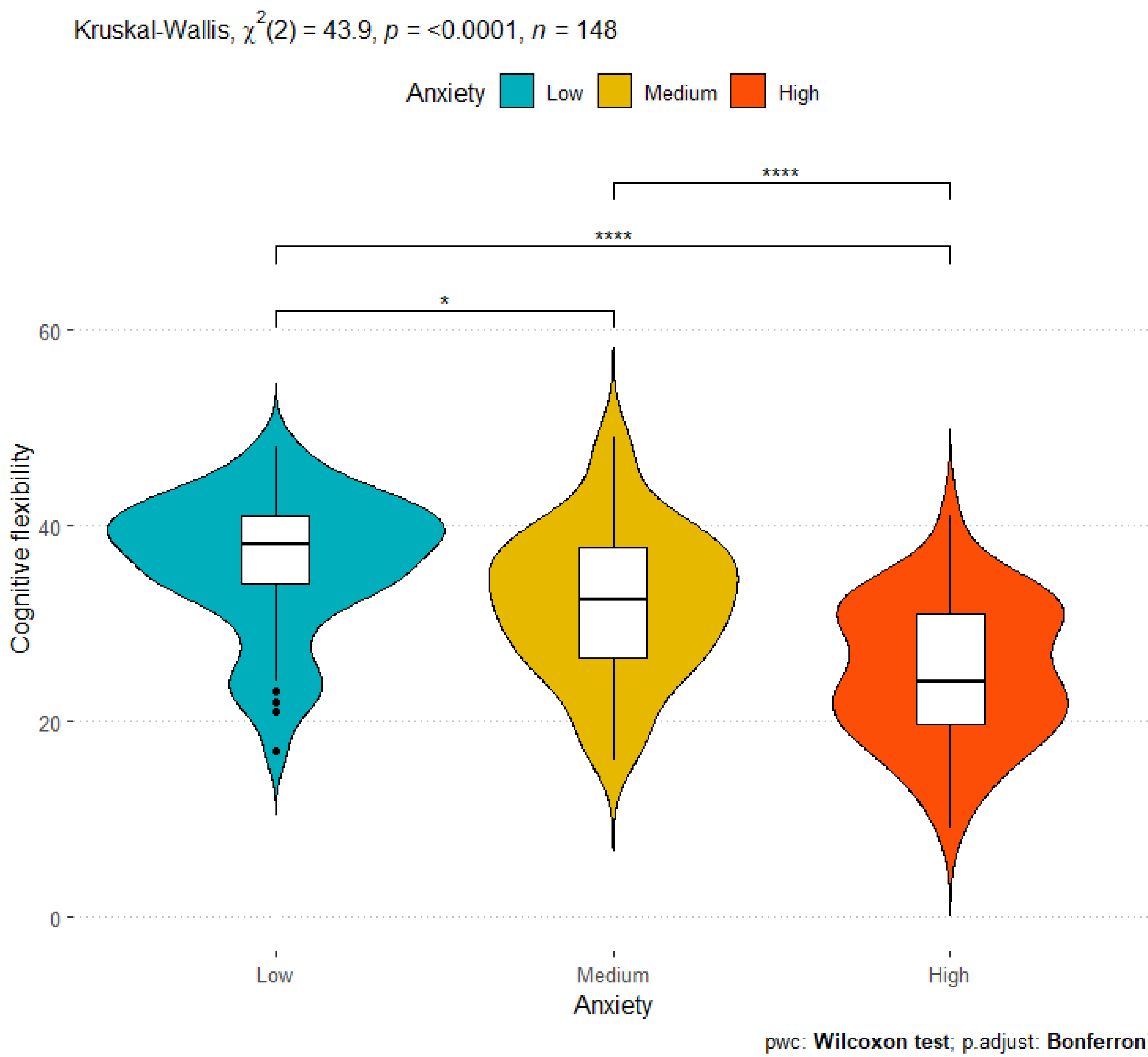

Figure 8. *Violin plots with boxplots to illustrate the between-group differences in cognitive flexibility by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

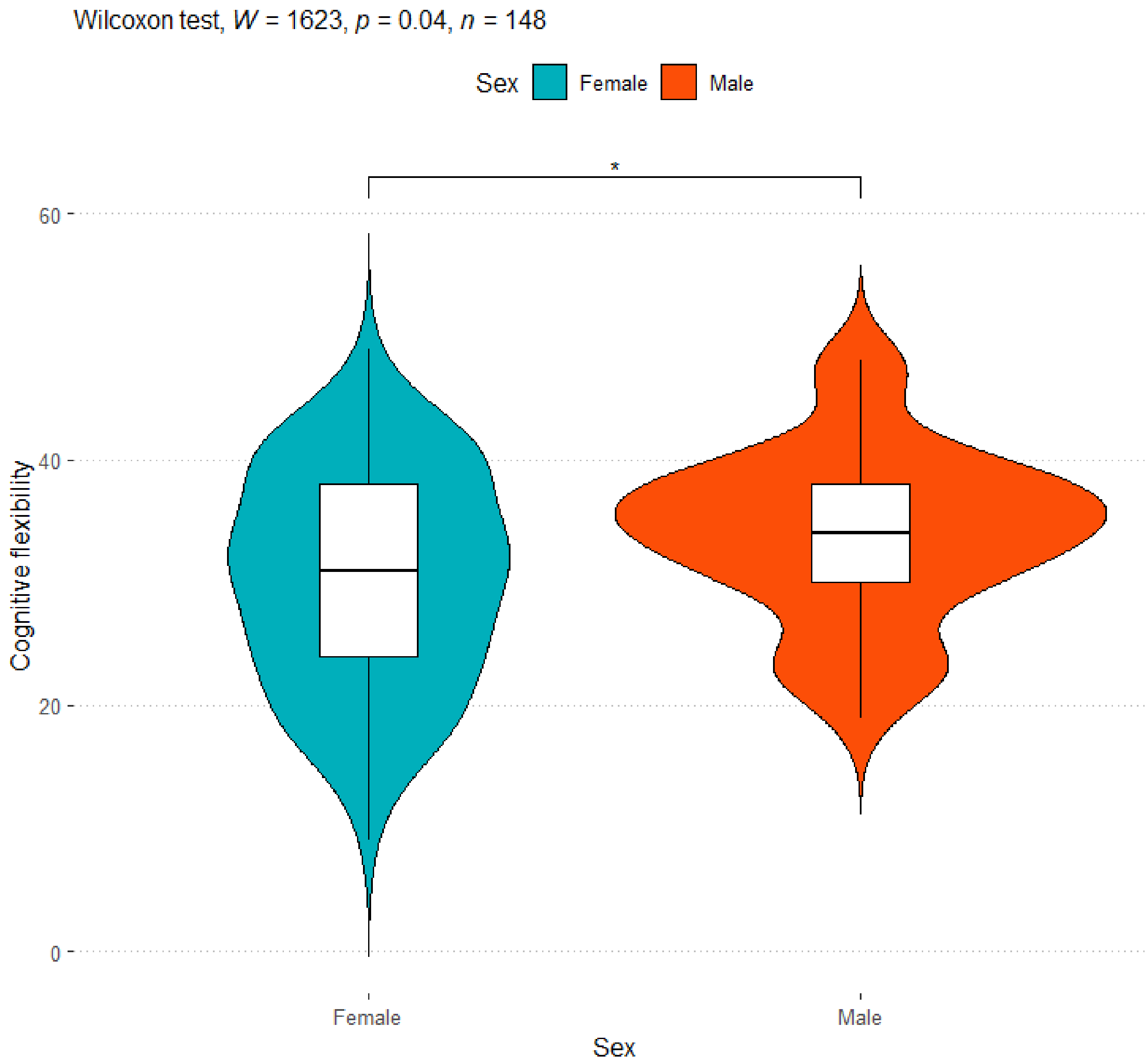

Figure 9. *Violin plots with boxplots to illustrate the between-group differences in cognitive flexibility by sex * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Cognitive avoidance

We used a three-way ANOVA test, which demonstrated a significant main effect of anxiety level on cognitive avoidance, $F(2, 136)=15.58$, $p<.001$. Nevertheless, none of the other main effects or interactions were significant, $p>.05$. Equally important, we used the Kruskal-Wallis test, which showed a significant main effect of anxiety level on cognitive avoidance when examined independently, $\chi2(2)=21.69$, $p<.001$ (see Figure 10). We conducted pairwise comparisons using the Wilcoxon rank-sum test with the Bonferroni correction. We found that 1) the magnitude of the difference between participants with low ($Mdn=69.5$, $IQR=29.5$) and medium ($Mdn=90$, $IQR=24.2$) anxiety was moderate, $W=782$, $p=.004$, $r=.32$, 2) the magnitude of the difference between participants with low and high ($Mdn=92$, $IQR=18.2$) anxiety was moderate, $W=572$, $p<.001$, $r=.45$, and 3) the magnitude of the difference between participants with medium and high anxiety was nonsignificant and small, $W=994$, $p=0.44$, $r=0.15$. The trend of the data shows that the higher the anxiety level, the greater the cognitive avoidance.

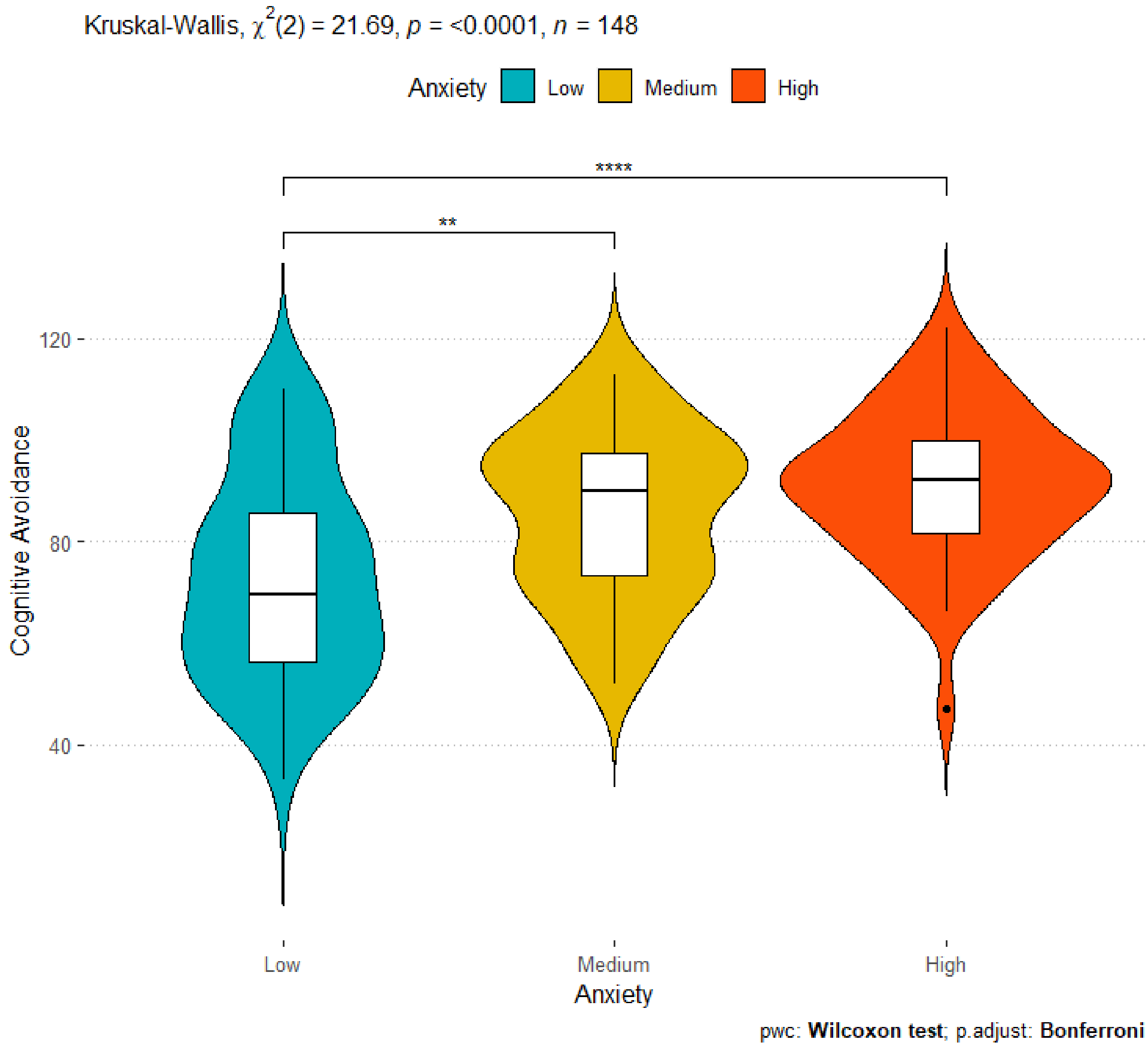

Figure 10. *Violin plots with boxplots to illustrate the between-group differences in cognitive avoidance by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Decentering

We used a three-way ANOVA test, which showed a significant main effect of anxiety level on decentering, $F(2, 136)=30.13$, $p<.001$. Nonetheless, the other main effects and interactions were not significant, $p>.05$. Then, we used the Kruskal-Wallis test, which demonstrated a significant main effect of anxiety level on decentering when examined independently, $\chi 2(2)=21.69$, $p<.001$ (see Figure 11). We performed pairwise comparisons using the Wilcoxon rank-sum test with the Bonferroni correction. We found that 1) the magnitude of the difference between participants with low (*Mdn*=40, *IQR*=5.75) and medium (*Mdn*=39, *IQR*=9) anxiety was nonsignificant and small, $W=1{,}423$, $p=.70$, $r=.12$, 2) the magnitude of the difference between participants with low and high (*Mdn*=32.5, *IQR*=6.25) anxiety was large, $W=2{,}073$, $p<.001$, $r=.63$, and 3) the magnitude of the difference between participants with medium and high anxiety was large, $W=1{,}923$, $p<.001$, $r=.52$. The trend of the data shows that the higher the anxiety level, the lower the decentering.

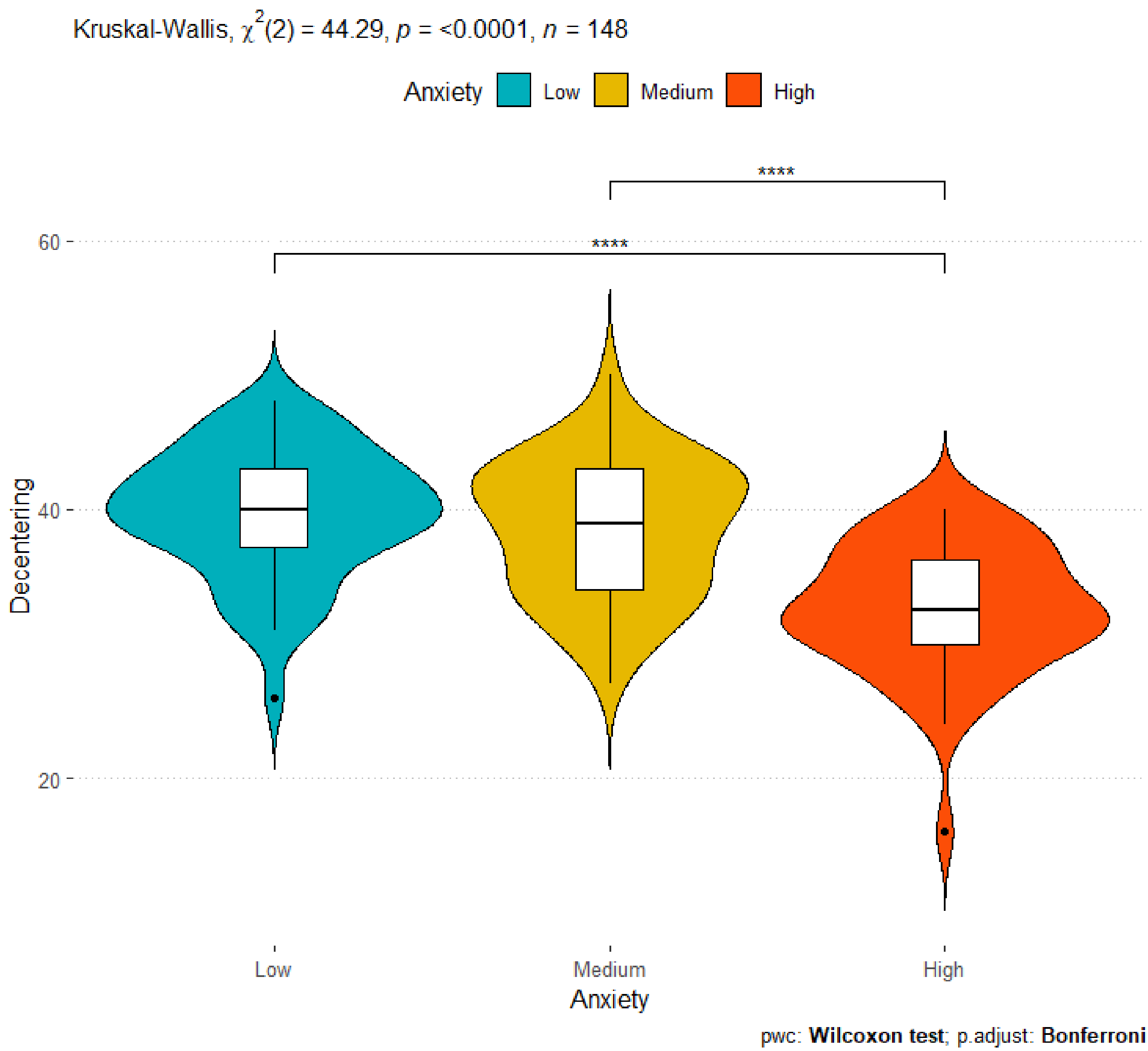

Figure 11. *Violin plots with boxplots to illustrate the between-group differences in decentering by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Dispositional mindfulness

We used a three-way ANOVA test, which demonstrated a significant main effect of anxiety level on dispositional mindfulness, $F(2, 136)=11.97$, $p<.001$ and a significant two-way interaction between anxiety level and employment status on dispositional mindfulness, $F(2, 136)=3.31$, $p=.040$. However, the other main effects and interactions were not significant, $p>.05$. On the one hand, we used the Kruskal-Wallis test, which showed a significant main effect of anxiety level on dispositional mindfulness when examined independently, $\chi 2(2)=21.12$, $p<.001$ (see Figure 12). We performed pairwise comparisons using the Wilcoxon rank-sum test with the Bonferroni correction. We found that 1) the magnitude of the difference between participants with low (*Mdn*=59, *IQR*=18.5) and medium anxiety (*Mdn*=54.5, *IQR*=15.8) was nonsignificant and small, $W=1{,}579$, $p=.071$, $r=.23$, 2) the magnitude of the difference between participants with low and high (*Mdn*=42.5, *IQR*=18.5) anxiety was moderate, $W=1{,}814$, $p<.001$, $r=.44$, and 3) the magnitude of the difference between participants with medium and high anxiety was small, $W=1{,}588$, $p=.018$, $r=.28$. The trend of the data shows that the higher the anxiety level, the lower the dispositional mindfulness.

On the other hand, we used a two-way ANOVA test, which demonstrated a marginally significant interaction effect of anxiety level and employment status on dispositional mindfulness when examined independently, $F(2, 142)=3.036$, $p=.051$ (see Figure 13). We performed pairwise comparisons using the estimated marginal means with the Bonferroni correction. In relation to the employed individuals, there were no differences in dispositional mindfulness regardless of the anxiety level, $p>.05$. With respect to the unemployed individuals, we found that 1) the magnitude of the difference between participants with low ($M=59.4$, $SE=2.44$) and medium anxiety ($M=53.1$, $SE=2.22$) was nonsignificant and small, $t(142)=1.84$, $p=.204$, Cohen's *d*=0.49, 2) the magnitude of the difference between participants with low and high (*M*=41.6, *SE*=2.40) anxiety was large, *t*(142)=5.15, *p*<.001, Cohen's *d*=1.32, and 3) the magnitude of the difference between participants with medium and high anxiety was large, *t*(142)=3.44, *p*=.003, Cohen's *d*=0.90. The trend of the data shows that the higher the anxiety level, the lower the dispositional mindfulness.

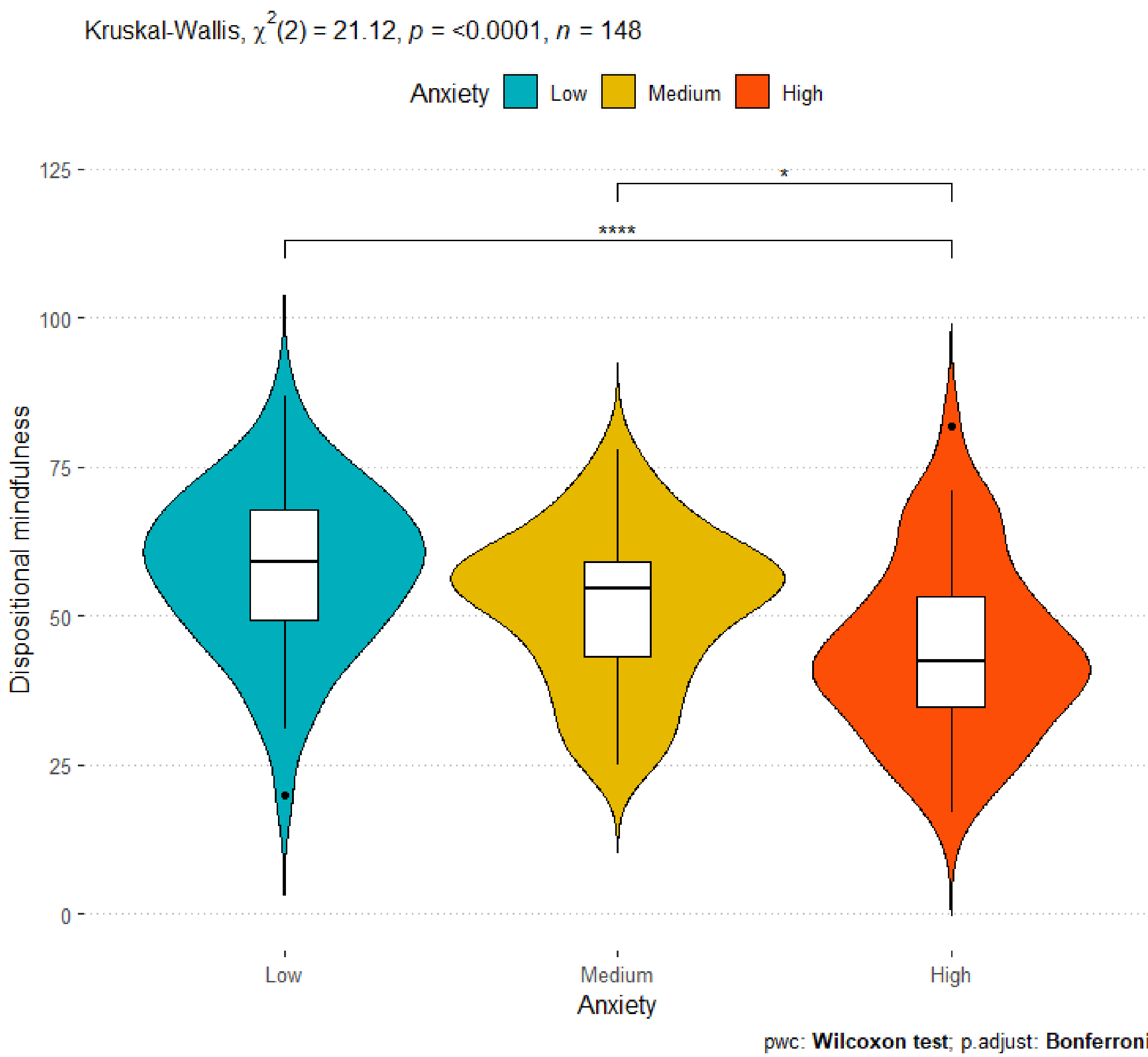

Figure 12. *Violin plots with boxplots to illustrate the between-group differences in dispositional mindfulness by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

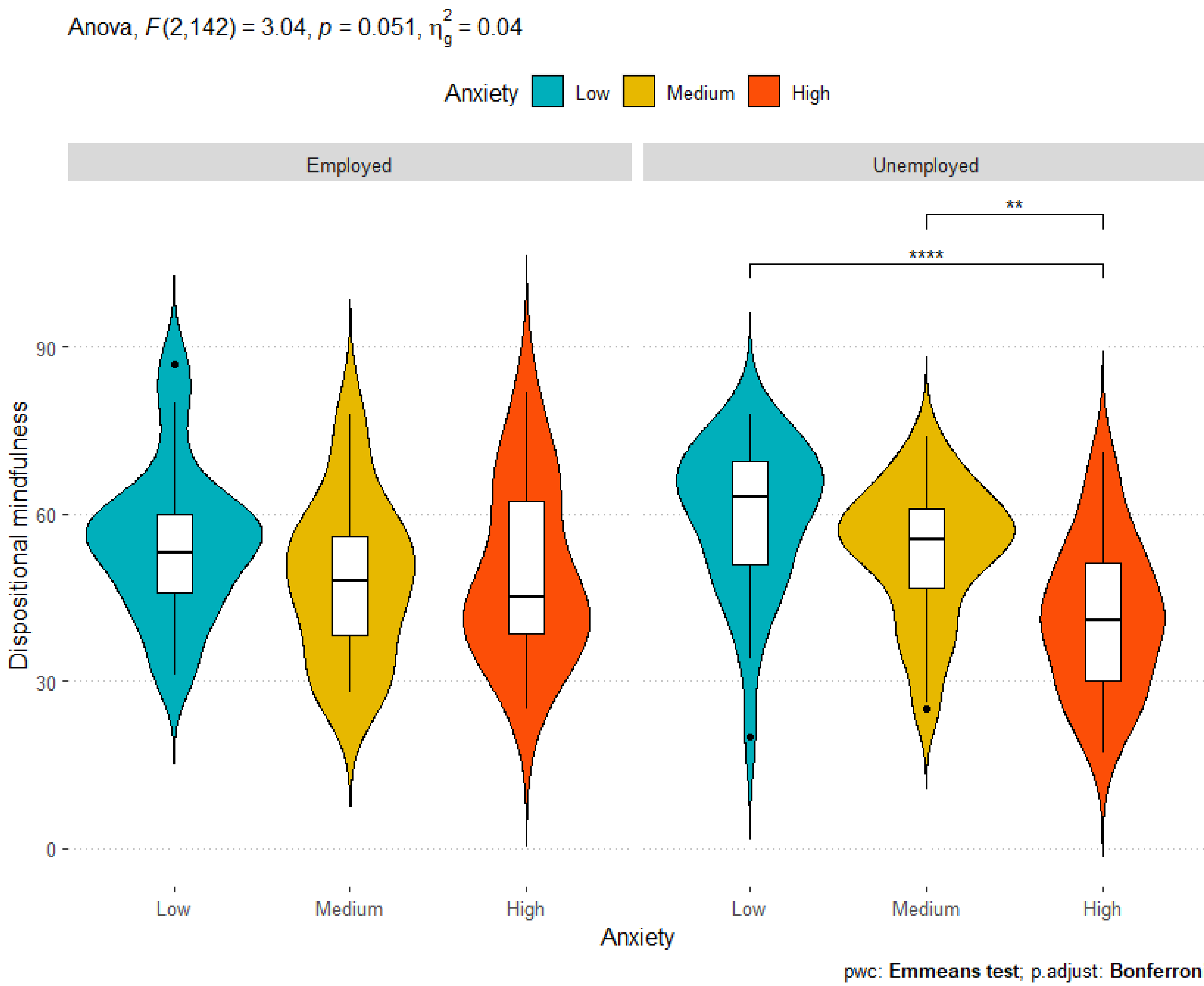

Figure 13. *Violin plots with boxplots to illustrate the between-group differences in dispositional mindfulness by anxiety level and employment status * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Personality characteristics in a subsample with extreme anxiety levels

We examined the personality characteristics in a subsample with extreme (low or high) anxiety levels. One participant who preferred not to answer the question about his/her sex was excluded from these analyses (N=98).

Cognitive flexibility

We used a three-way ANOVA test, which showed significant main effects of anxiety level, $F(1, 90)=56.62$, $p<.001$ and sex, $F(1, 90)=4.47$, $p=.037$ on cognitive flexibility. Nevertheless, none of the other main effects or interactions were significant, $p>.05$. Then, we examined the main effect of anxiety level independently. Specifically, we used the Wilcoxon rank-sum test, which demonstrated a significant and large difference between participants with low (Mdn=38, IQR=7) and high (Mdn=24, IQR=11.2) anxiety levels, W=2,084, $p<.001$, r=.64 (see Figure 14). Therefore, higher anxiety levels were associated with lower cognitive flexibility scores. Next, we examined the main effect of sex independently. Again, we used the Wilcoxon rank-sum test, which showed a nonsignificant and small difference between male (Mdn=34, IQR=7.5) and female (Mdn=31, IQR=15.5) participants, W=675, p=.12, r=.16 (see Figure 15).

Figure 14. *Violin plots with boxplots to illustrate the between-group differences in cognitive flexibility by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

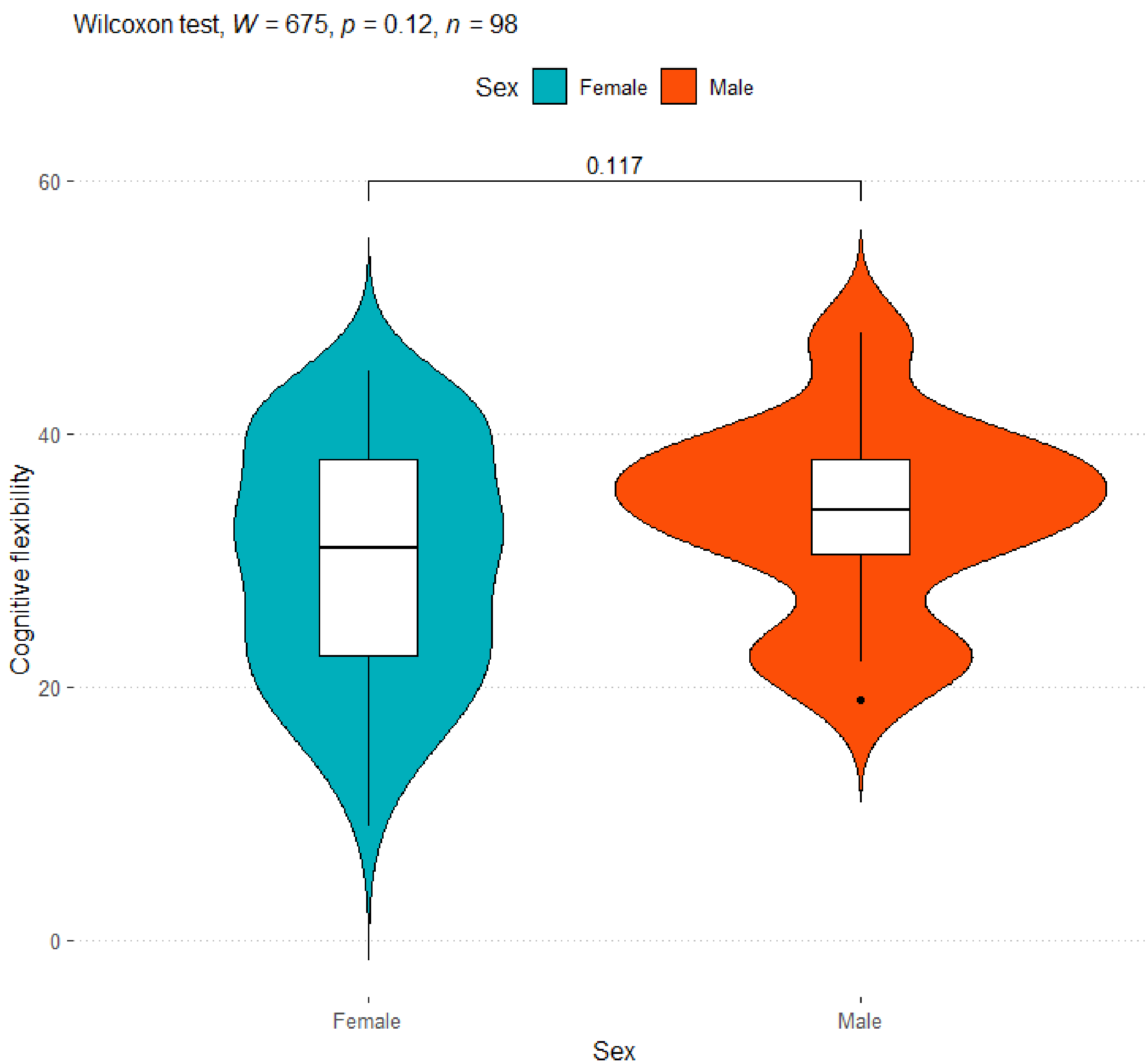

Figure 15. *Violin plots with boxplots to illustrate the between-group differences in cognitive flexibility by sex.*

Cognitive avoidance

We used a three-way ANOVA test, which showed a significant main effect of anxiety level on cognitive avoidance, $F(1, 90)=28.58$, $p<.001$. However, none of the other main effects or interactions were statistically significant, $p>.05$. Then, we examined the main effect of anxiety level independently. We used the Wilcoxon rank-sum test, which demonstrated a significant and moderate difference between participants with low ($Mdn=69.5$, $IQR=29.5$) and high ($Mdn=92$, $IQR=18.2$) anxiety levels, $W=572$, $p<.001$, $r=.45$ (see Figure 16). Thus, higher anxiety levels were related with greater cognitive avoidance scores.

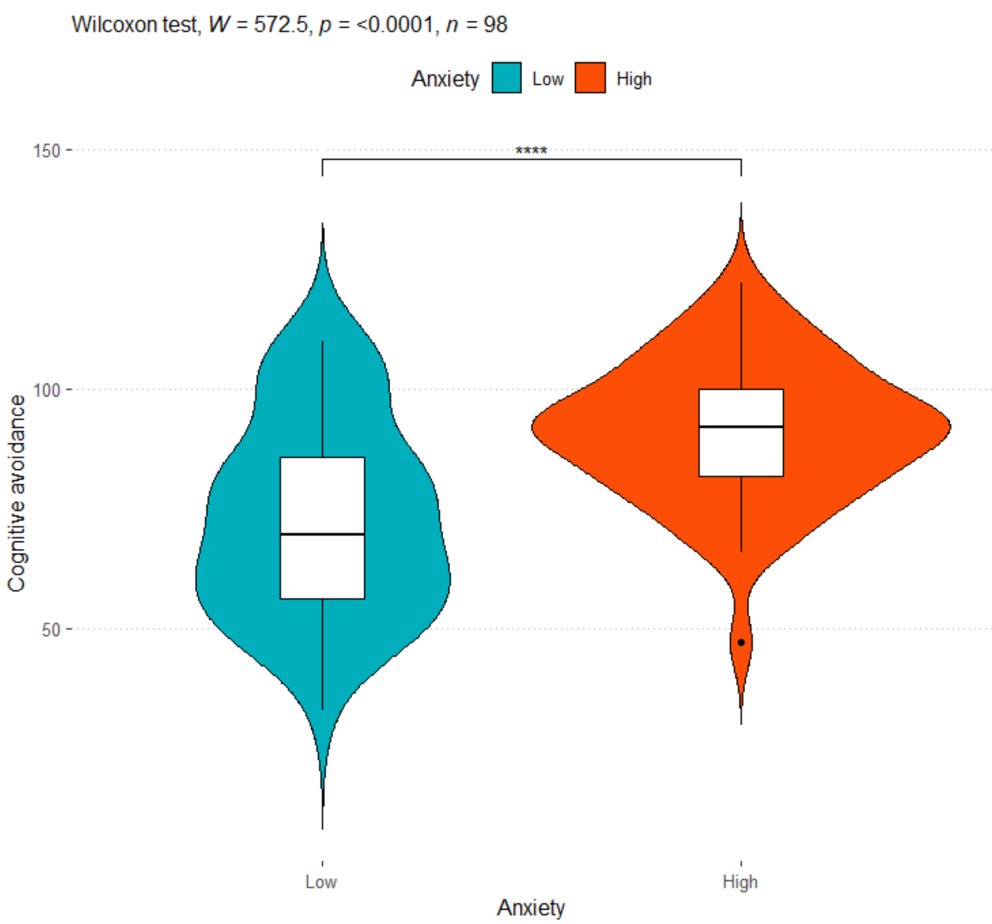

Figure 16. *Violin plots with boxplots to illustrate the between-group differences in cognitive avoidance by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Decentering

We used a three-way ANOVA test, which demonstrated a significant main effect of anxiety level on decentering, $F(1, 90)=56.34$, $p<.001$. Nevertheless, none of the other main effects or interactions were statistically significant, $p>.05$. Moreover, we examined the main effect of anxiety level independently. We used the Wilcoxon rank-sum test, which showed a significant and large difference between participants with low (*Mdn*=40, *IQR*=5.75) and high (*Mdn*=32.5, *IQR*=6.25) anxiety levels, $W=2{,}074$, $p<.001$, $r=.63$ (see Figure 17). Therefore, higher anxiety levels were associated with lower decentering scores.

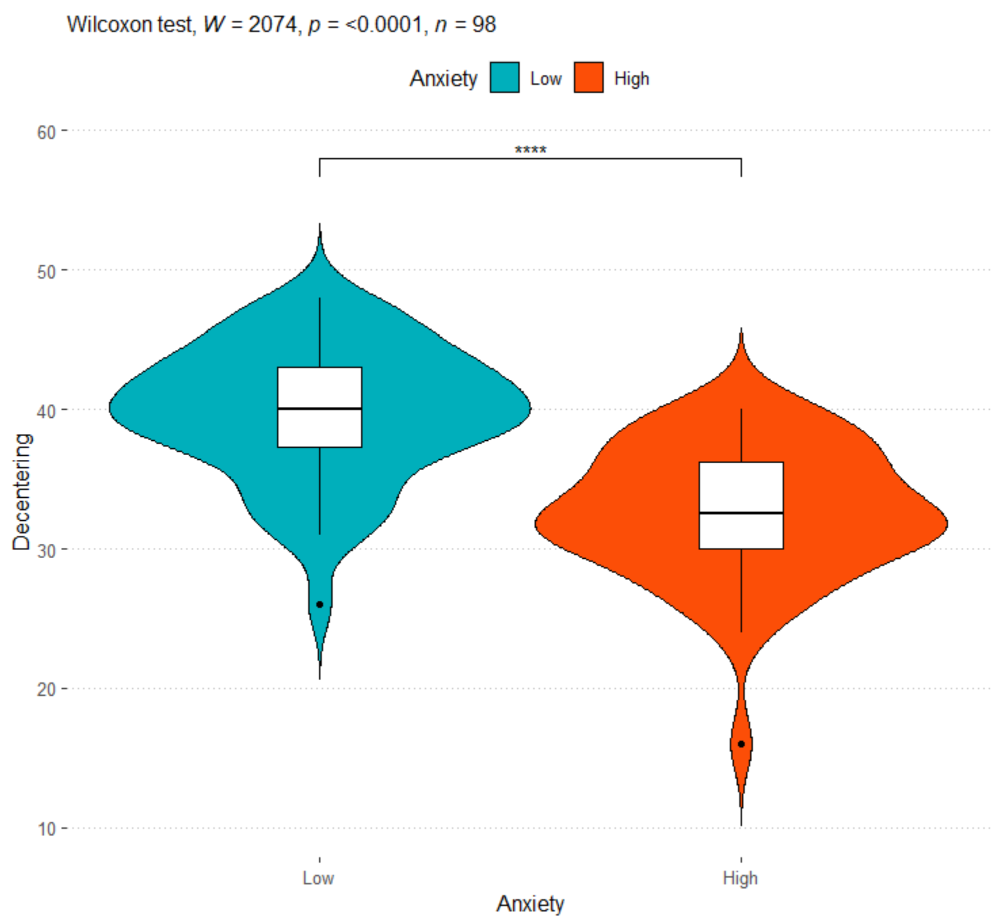

Figure 17. *Violin plots with boxplots to illustrate the between-group differences in decentering by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Dispositional mindfulness

We used a three-way ANOVA test, which demonstrated a significant main effect of anxiety level on dispositional mindfulness, $F(1, 90)=22.17$, $p<.001$ and a significant two-way interaction between anxiety level and employment status on dispositional mindfulness, $F(1, 90)=4.28$, $p=.041$. However, the other main effects and interactions were not significant, $p>.05$. On the one hand, we examined the main effect of anxiety level independently. Specifically, we used the Wilcoxon rank-sum test, which showed a significant and moderate difference between the low ($Mdn=59$, $IQR=18.5$) and high ($Mdn=42.5$, $IQR=18.5$) anxiety groups, $W=1{,}814$, $p<.001$, $r=.44$ (see Figure 18). Therefore, higher anxiety levels were related with lower dispositional mindfulness scores.

On the other hand, we used a two-way ANOVA test, which demonstrated a significant interaction effect of anxiety level and employment status on dispositional mindfulness when examined independently, $F(1, 94)=4.27$, $p=.041$ (see Figure 19). We performed pairwise comparisons using the estimated marginal means. With respect to the employed individuals, there were no differences in dispositional mindfulness regardless of the anxiety level, $p>.05$. In relation to the unemployed individuals, we found a significant and large difference between the low ($M=59.4$, $SE=2.50$) and high ($M=41.6$, $SE=2.46$) anxiety groups, $t(94)=5.05$, $p<.001$, Cohen's $d=1.32$. The trend of the data shows that the higher the anxiety level, the lower the dispositional mindfulness.

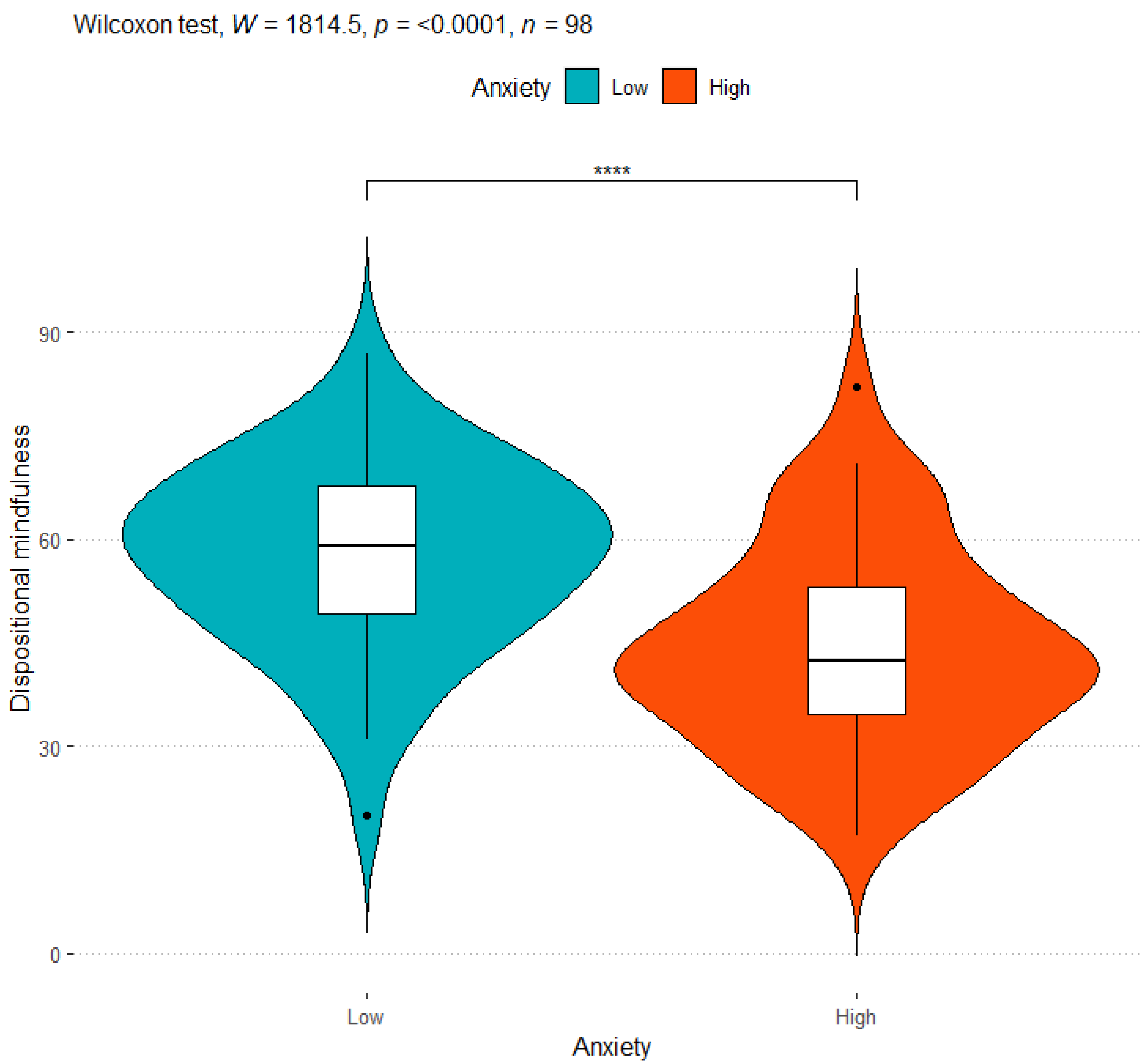

Figure 18. *Violin plots with boxplots to illustrate the between-group differences in dispositional mindfulness by anxiety level * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

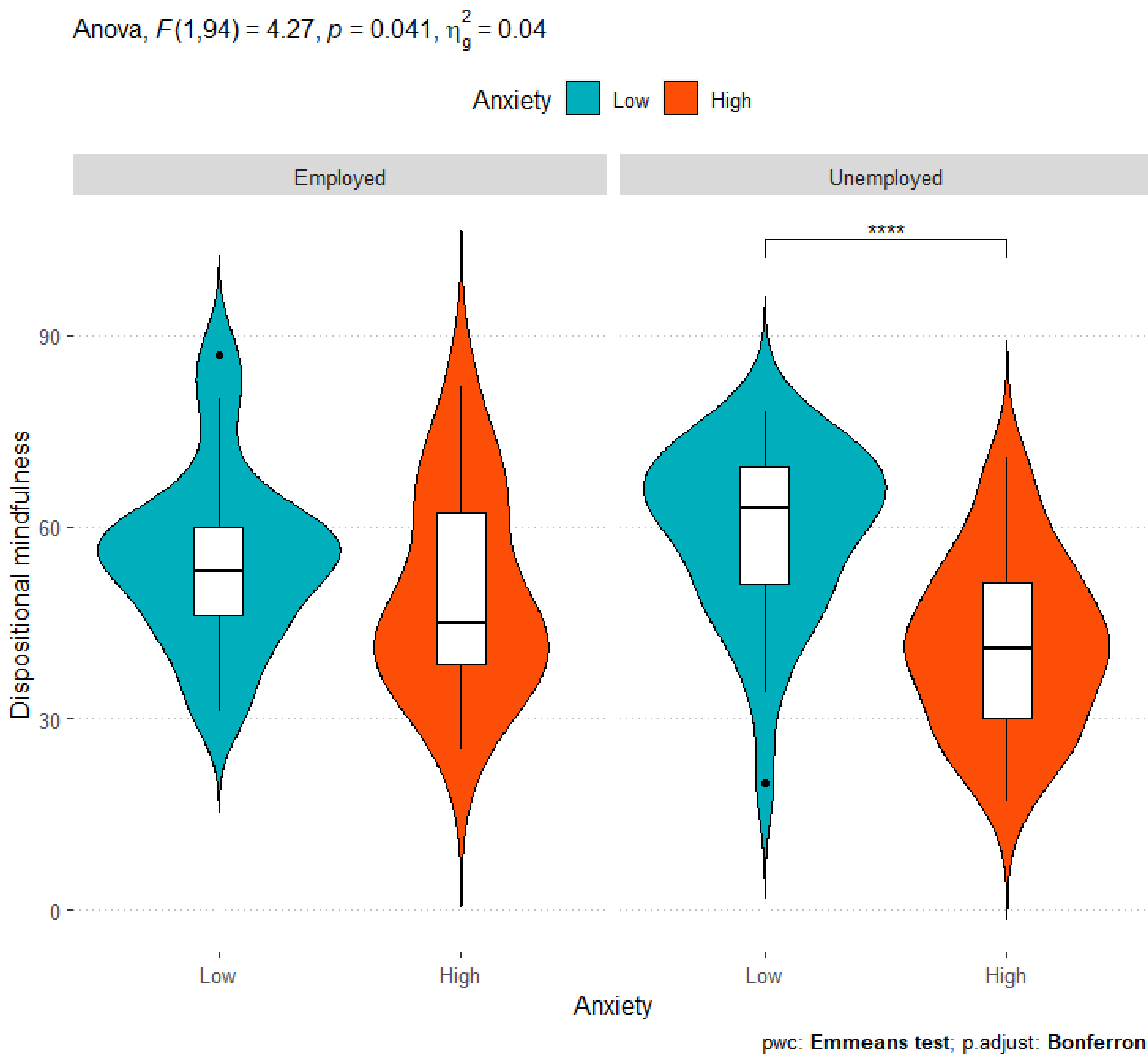

Figure 19. *Violin plots with boxplots to illustrate the between-group differences in dispositional mindfulness by anxiety level and employment status * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Within-subject's differences in the cognitive computerized tasks

To examine whether there were within-subject's differences across each of the cognitive computerized task's conditions or times, we used several Wilcoxon signed-rank tests.

Emotional counting Stroop

There were no within-subject's differences in reaction times (ms) across the neutral (*Mdn*=722, *IQR*=116) and emotional (*Mdn*=725, *IQR*=107) conditions (*W*=5,608, *p*=.971, *r*=.01; see Figure 20). Since the emotional counting Stroop interference effect did not show the expected within-subject's difference, we excluded this measure from further analyses.

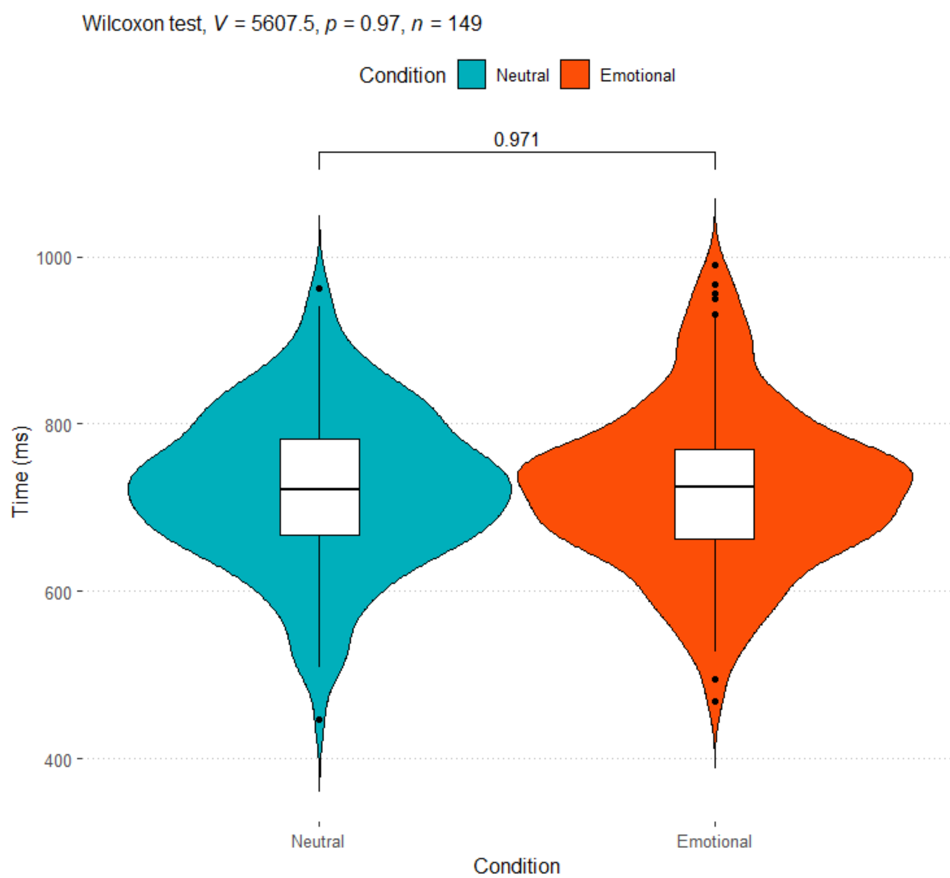

Figure 20. *Violin plots with boxplots to illustrate the within-subject's differences across the neutral and emotional conditions of the emotional counting Stroop task.*

Task-switching alternating

There was a large within-subject's difference in reaction times (ms) across the task-repeat (*Mdn*=986, *IQR*=304) and task-switch (*Mdn*=1,317, *IQR*=399) conditions (W=258, p<.001, r=.83; see Figure 21). Participants took longer to respond to the task-switch condition compared to the task-repeat condition. Since switch cost demonstrated the expected within-subject's difference, we included this measure in further analyses.

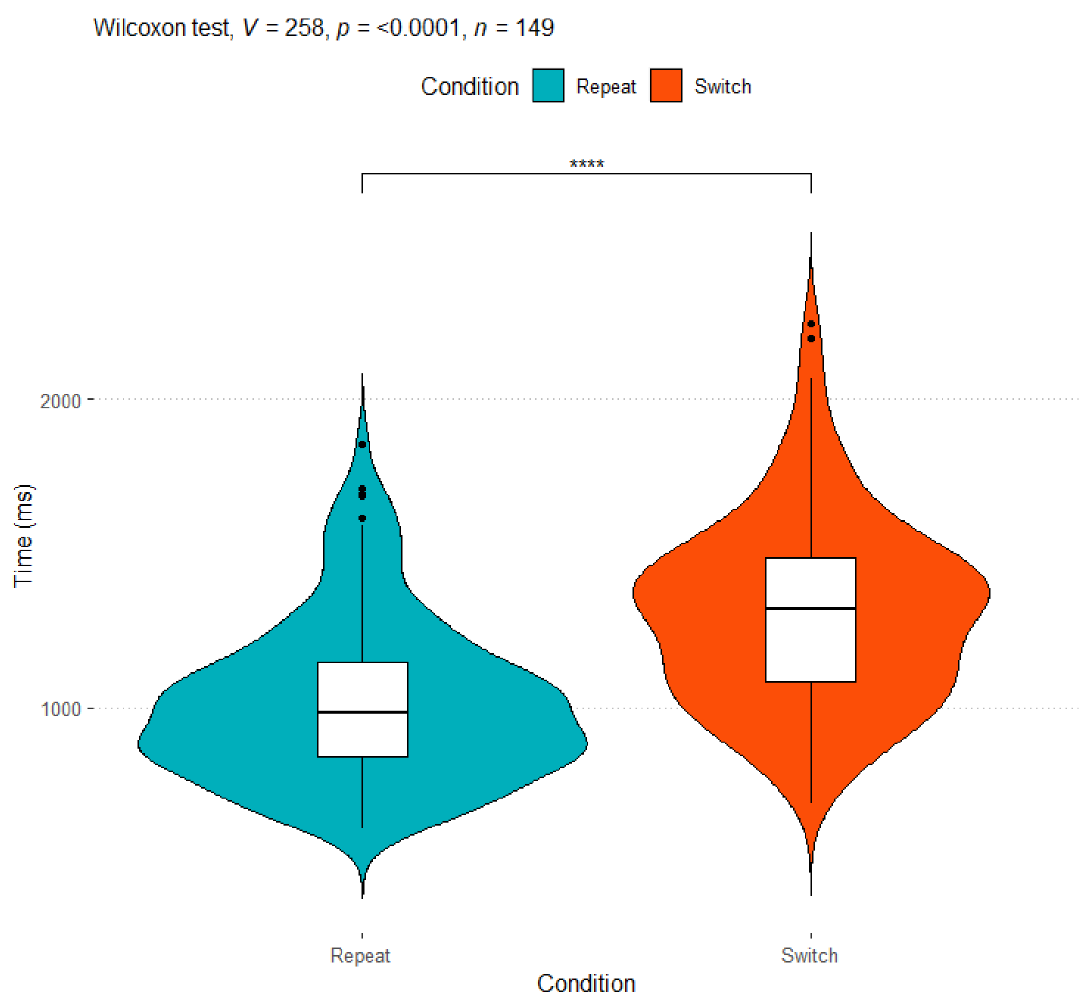

Figure 21. *Violin plots with boxplots to illustrate the within-subject's differences across the repeat and switch conditions of the task-switching alternating task * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Go/no-go reversal learning

There was a moderate within-subject's difference across the first (*Mdn*=2.76, *IQR*=2.01) and second (*Mdn*=3.26, *IQR*=2.24) half of the recovery phase (*W*=954, *p*<.001, *r*=.45; see Figure 22). Participants obtained higher reversal learning scores in the second half of the recovery phase compared to the first half. Since reversal learning demonstrated the expected within-subject's difference, we included this measure in further analyses.

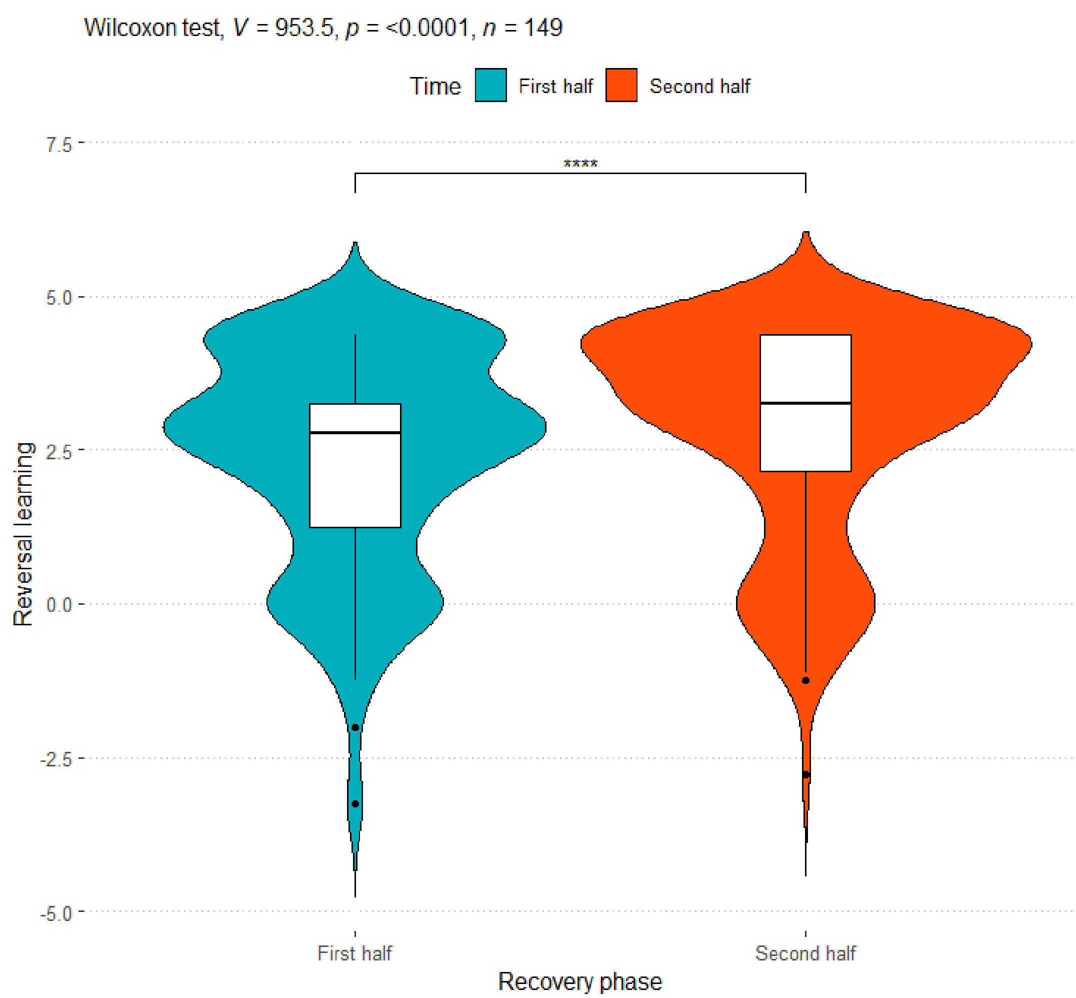

Figure 22. *Violin plots with boxplots to illustrate the within-subject's differences across the first and second half of the recovery phase in the go/no-go reversal learning task * p<.05 ** p<.01 *** p<.001 **** p<.0001.*

Performance in the cognitive computerized tasks

We examined between-group differences by anxiety level, sex, and employment status in the task-switching alternating and go/no-go reversal learning tasks using several three-way ANOVAs. One participant who preferred not to answer the question about his/her sex was excluded from the analysis. We performed the three-way ANOVAs both in the main sample (N=148) and a subsample of participants with extreme (low or high) anxiety levels (N=98). However, no significant main effects or interactions were found in any of the computerized cognitive tasks regardless of the sample used, p>.05.

Descriptive statistics and Pearson correlations among variables

The descriptive statistics and Pearson correlations among variables are presented in Table 6. Interested readers can conduct secondary analyses of the two-step SEM modeling approach using this correlation matrix or by requesting the archived case-level data without identifiers via email (jose.maldonado16@upr.edu). First, in the measurement model, each latent construct was defined using three continuous composite variables. Then, in the structural model, we tested the three main hypotheses of the study. A two-step modeling approach is usually preferred because it assures that the latent constructs are correctly measured before analyzing the structural relations in the model. This study's model is a partially latent structural regression model because at least one variable in its structural part is a single indicator (e.g., switch cost and reversal learning).

Two-step analysis of a partially latent structural model of trait anxiety and cognitive control

The general approach that best describes the application of two-step SEM modeling is to compare alternative models, rather than being strictly confirmatory (Appelbaum et al., 2018). We submitted the correlations and standard deviations in Table 6 to lavaan (Rosseel, 2012) for analysis with the *sem* function. The first model analyzed with maximum likelihood estimation was a standard one-factor CFA model with 15 indicators. Specifically, we used robust standard errors, and Satorra and Bentler's (2001) adjusted fit indices for all models considering the non-normality of the data. The *sem* function in *lavaan* (Rosseel, 2012) allows a default maximum number of 150 iterations. Estimation in *lavaan* (Rosseel, 2012) converged to an admissible solution. Values of selected fit statistics for this initial measurement model are reported in Table 7. The fit of the one-factor CFA model is poor. For example, the model fails both the exact-fit and close-fit tests (p<.001 for both), and the lower bound of the RMSEA 90% confidence interval, or .161, exceeds .10, a value that may suggest poor fit (see the table).

Next, we specified the measurement model as a standard five-factor CFA model (see Figure 23). Estimation in *lavaan* (Rosseel, 2012) converged to an admissible solution. Values of selected fit statistics for this five-factor CFA model are listed in Table 7. The relative improvement in fit of the five-factor CFA model over that of the one-factor CFA model is statistically significant, $\chi2_D(10)=286.33$, p<.001. However, the model fails both the exact-fit test, p<.001 and close-fit test, p=.001, and the upper bound of the RMSEA 90% confidence interval, or .106, exceeds .10, which may indicate a poor global fit (see the table).

Table 6. *Means, standard deviations, and Pearson correlations among variables*

Variable	*M*	*sd*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. STAI-1	9.88	4.36	—															
2. STAI-2	9.71	4.45	.81	—														
3. STAI-3	9.60	4.17	.80	.75	—													
4. CFI-1	14.26	3.93	-.59	-.54	-.57	—												
5. CFI-2	8.10	3.12	-.58	-.56	-.60	.70	—											
6. CFI-3	8.81	3.01	-.30	-.25	-.38	.54	.41	—										
7. CAQ-1	19.01	4.45	.37	.35	.51	-.35	-.38	-.30	—									
8. CAQ-2	13.99	4.49	.46	.41	.53	-.45	-.50	-.39	.46	—								
9. CAQ-3	18.58	4.81	.36	.33	.55	-.29	-.39	-.32	.62	.63	—							
10. EQ-1	12.48	2.33	-.42	-.47	-.41	.40	.31	.27	-.13	-.20	-.27	—						
11. EQ-2	14.62	3.00	-.37	-.40	-.40	.50	.30	.37	-.36	-.25	-.23	.44	—					
12.EQ-3	9.91	1.92	-.48	-.50	-.41	.36	.31	.13	-.16	-.23	-.14	.44	.44	—				
13. MAAS-1	16.51	5.74	-.29	-.29	-.37	.16	.19	.24	-.33	-.29	-.35	.18	.27	-.00	—			
14. MAAS-2	17.69	5.76	-.37	-.35	-.41	.22	.21	.17	-.34	-.28	-.27	.16	.35	.07	.73	—		
15. MAAS-3	16.99	4.86	-.33	-.30	-.33	.26	.27	.29	-.24	-.22	-.22	.25	.36	.13	.68	.73	—	
16. SC	286.55	221.77	.05	.09	-.06	-.03	-.03	.02	-.14	-.10	-.09	-.02	-.03	-.15	-.01	-.00	-.08	—
17. RL	0.51	1.10	.00	.04	-.08	.07	.14	.07	.01	-.11	-.08	.00	-.00	-.02	.08	.05	.09	-.06

Note. *M* and *sd* are used to represent mean and standard deviation, respectively. STAI-1=Trait anxiety composite 1, STAI-2=Trait anxiety composite 2, STAI-3=Trait anxiety composite 3, CFI-1=Cognitive flexibility composite 1, CFI-2=Cognitive flexibility composite 2, CFI-3=Cognitive flexibility composite 3, CAQ-1=Cognitive avoidance composite 1, CAQ-2=Cognitive avoidance composite 2, CAQ-3=Cognitive avoidance composite 3, EQ-1=Decentering composite 1, EQ-2=Decentering composite 2, EQ-3=Decentering composite 3, MAAS-1=Dispositional mindfulness composite 1, MAAS-2=Dispositional mindfulness composite 3, CI=Cognitive interference, SC=Switch cost, RL=Reversal learning. To prevent an ill-scaled covariance matrix related to variables with extremely high variances, SC was rescaled by multiplying each score by the product of the variance and a constant of .001 squared. For example: $s^2_{\text{SC\_rescaled}}$ = SC * (.001^2 * 221.77^2). Rescaling a variable in this way changes its mean and variance but not its correlation with other variables, SC_rescaled (*M*=14.00, *SD*=10.80).

Inspection of the residuals for the five-factor CFA model indicated moderate local fit problems (see Table 8). For example, eighteen absolute correlation residuals exceeded .10. The ten largest error covariance modification indexes for the five-factor CFA model are presented in Table 9. Four of these results were for the error covariances between the following pairs of indicator composite variables: CAQ-1 and CAQ-2 (11.93), STAI-1 and STAI-2 (7.47), STAI-3 and CAQ-3 (13.41), and CFI-1 and EQ-2 (8.53).

Because it seems reasonable that common item content across CAQ-1 and CAQ-2 could explain shared error variance, we respecified the five-factor CFA model by allowing the error covariances between this pair of variables to be freely estimated in a third analysis. Estimation in *lavaan* (Rosseel, 2012) converged to an admissible solution. It's fit to the data was statistically better than that of the five-factor CFA model with no correlated errors, $\chi 2_D(1)=16.53$, $p<.001$ (see Table 7). However, both the exact-fit ($p<.001$) and close-fit ($p=.005$) hypotheses were rejected for this measurement model.

For the same reasons as above, we allowed the error covariances between STAI-1 and STAI-2 to be freely estimated in a fourth analysis. Estimation in *lavaan* (Rosseel, 2012) converged to an admissible solution. The relative fit of this model was significantly better than the third model, $\chi 2_D(1)=5.64$, $p=.018$ (see Table 7). Nonetheless, both the exact-fit ($p<.001$) and close-fit ($p=.008$) hypotheses were rejected for this measurement model.

Table 7. *Values of selected fit statistics for two-step testing of a partially structural regression model of trait anxiety and cognitive control*

Model	$\chi2_M$ standard	$\chi2_M$ robust	df_M	*p*	$\chi2_D$	Df_D	*p*	RMSEA (90% CI)	CFI	SRMR
<u>Measurement model</u>										
One factor	522.60	502.94	90	<.001	_	_	_	.175 [0.161, .190]	.651	.121
Five-factor	173.11	170.32	80	<.001	286.33	10	<.001	.087 [.069, .105]	.924	.063
Five-factor, $E_{CAQ-1} \leftrightarrow E_{CAQ-2}$	158.78	155.93	79	<.001	16.53	1	<.001	.081 [.062, .099]	.935	.060
Five-factor, $E_{CAQ-1} \leftrightarrow E_{CAQ-2}$, $E_{STAI-1} \leftrightarrow E_{STAI-2}$	152.61	150.01	78	<.001	5.64	1	.018	.079 [.060, .097]	.939	.058
Five-factor, $E_{CAQ-1} \leftrightarrow E_{CAQ-2}$, $E_{STAI-1} \leftrightarrow E_{STAI-2}$, $E_{STAI-3} \leftrightarrow E_{CAQ-3}$	139.52	136.92	77	<.001	14.70	1	<.001	.072 [.052, .092]	.949	.057

Model	$\chi 2_M$ standard	$\chi 2_M$ robust	df_M	p	$\chi 2_D$	Df_D	p	RMSEA (90% CI)	CFI	SRMR
Five-factor, E_{CAQ-1} E_{CAQ-2}, E_{STAI-1} E_{STAI-2}, E_{STAI-3} E_{CAQ-3} E_{CFI-1} E_{EQ-2}	131.61	129.35	76	<.001	6.97	1	.008	.069 [.048, .088]	.955	.058
<u>Structural model</u>										
Parallel mediation model	166.44	167.01	104	<.001	—	—	—	.064 [.045, .081]	.947	.062
Directs effects model	172.27	173.10	110	<.001	6.01	6	.423	.062 [.044, .079]	.947	.064
Indirect effects model	168.99	169.74	106	<.001	2.70	2	.259	.064 [.045, .081]	.946	.063

Note. *CI* = Confidence interval. X^2_M standard = standard test statistics. X^2_M robust = robust test statistics. The $\chi 2_D$ column reports the scaled chi-square difference test between standard test statistics, not the robust test statistics that should be reported per model. A robust difference test is a function of two standard (not robust) statistics. The parallel mediation model has twelve direct paths. The direct effects model has six direct paths. The indirect effects model has ten direct paths. The results were computed using the *lavaan* package in R.

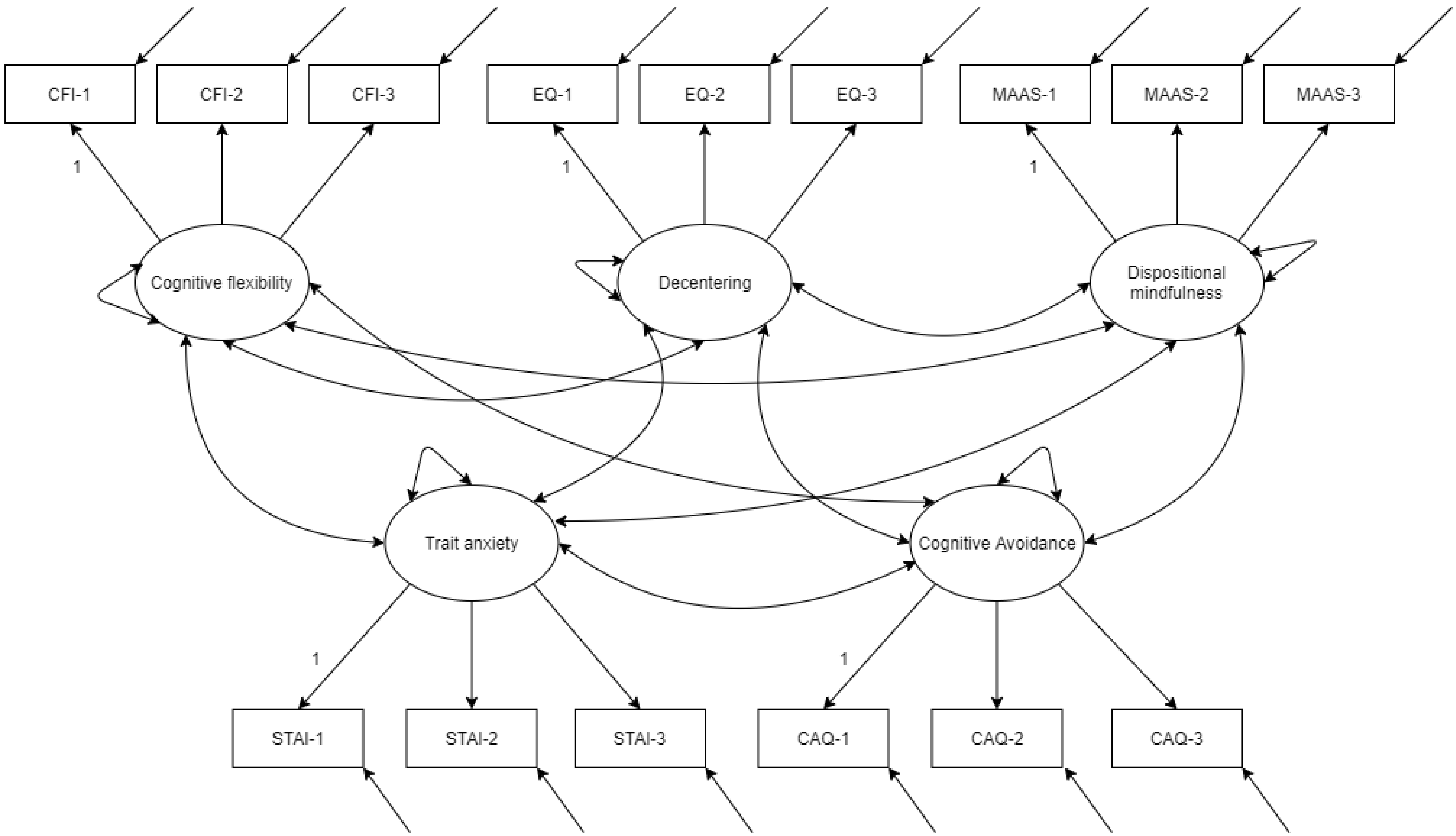

Figure 23. *Original five-factor measurement component in a partially structural regression model of trait anxiety and cognitive control with compact symbolism for indicator error terms*

Table 8. *Correlation residuals for the five-factor measurement model of trait anxiety and cognitive control*

Indicator	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. STAI-1	-													
2. STAI-2	.02	-												
3. STAI-3	-.01	-.02	-											
4. CFI-1	.01	.03	.01	-										
5. CFI-2	-.03	-.04	-.07	-.01	-									
6. CFI-3	.09	**.12**	.00	.04	-.05	-								
7. CAQ-1	-.03	.03	**.12**	.02	-.04	-.06	-							
8. CAQ-2	.03	-.00	**.11**	-.06	**-.14**	**-.14**	-.08	-						
9. CAQ-3	**-.10**	**-.11**	**.10**	**.14**	.00	-.04	.04	.01	-					
10. EQ-1	.02	-.06	.02	.01	-.04	.02	.02	.01	-.04	-				
11. EQ-2	.06	.02	.03	**.11**	-.06	**.12**	**-.16**	-.03	.01	-.00	-			
12.EQ-3	-.05	-.08	.02	-.03	-.05	**-.13**	.04	-.01	.09	.00	.00	-		
13. MAAS-1	.05	.04	-.04	-.07	-.02	.09	-.08	-.02	-.06	-.01	.08	**-.19**	-	
14. MAAS-2	-.01	-.00	-.05	-.03	-.01	.02	-.08	.01	.04	-.04	**.15**	**-.13**	-.01	-
15. MAAS-3	.01	.03	.00	.04	.06	**.14**	.01	.04	.07	.06	**.17**	-.06	.01	.00

Note. Absolute correlation residuals above .10 are presented in boldface. The correlation residuals were computed using the *lavaan* package in R.

Table 9. *The ten largest error covariance modification indexes for the five-factor measurement model of trait anxiety and cognitive control*

Path	MI
$E_{STAI\text{-}3}$ $E_{CAQ\text{-}3}$	**13.41**
$E_{CAQ\text{-}1}$ $E_{CAQ\text{-}2}$	**11.92**
$E_{CAQ\text{-}1}$ $E_{EQ\text{-}2}$	9.01
$E_{CFI\text{-}1}$ $E_{CAQ\text{-}3}$	8.86
$E_{CFI\text{-}1}$ $E_{EQ\text{-}2}$	**8.53**
$E_{STAI\text{-}1}$ $E_{STAI\text{-}2}$	**7.47**
$E_{CFI\text{-}2}$ $E_{EQ\text{-}2}$	6.86
$E_{CAQ\text{-}1}$ $E_{CAQ\text{-}3}$	6.43
$E_{CAQ\text{-}3}$ $E_{EQ\text{-}1}$	6.19
$E_{CFI\text{-}3}$ $E_{EQ\text{-}2}$	5.54

Note. MI = Modification index. The error covariance paths that were added to the final five-factor CFA model are represented in boldface. The results were computed using the *lavaan* package in R.

Based on the literature that examined the direct and indirect links between trait anxiety and cognitive avoidance (Mahoney et al., 2018; Ruiter & Brosschot, 1994; Spinhoven et al.,

2017) and the high correlation between factors obtained in this study (*r*=.63), specifying that STAI-3 and CAQ-3 share error variance is plausible. Therefore, we allowed the error covariances between this pair of composite indicators to be freely estimated in a fifth analysis. Estimation in lavaan (Rosseel, 2012) converged to an admissible solution. The relative fit of this model was significantly improved compared to the fourth model, $\chi 2_D(1)=14.70$, $p<.001$ (see Table 7). However, the exact-fit ($p<.001$) and close-fit ($p=.035$) hypotheses were also rejected for this measurement model.

Lastly, both cognitive flexibility and decentering are adaptive cognitive regulation abilities that involve changing one's rigid or centered maladaptive cognitive strategies to balanced or openminded thinking styles (Dennis & Vander-Wal, 2010, VandenBos, 2015). These factors obtained a high correlation in this study (*r*=.68). Thus, specifying that CFI-1 and EQ-2 share error variance is reasonable. For these reasons, we allowed the error covariances between this pair of composite indicators to be freely estimated in a sixth analysis. Estimation in lavaan (Rosseel, 2012) converged to an admissible solution. The relative fit of this model was significantly better than the fifth model, $\chi 2_D(1)=6.97$, $p=.008$ (see Table 7). Although the exact-fit hypothesis was rejected ($p<.001$), the close-fit hypothesis was not rejected for the respecified measurement model ($p=.068$). Values of other fit statistics were generally favorable, *RMSEA*=.069, 90% *CI* [.048, .088], *CFI*=.955, *SRMR*=.058. Furthermore, thirteen absolute correlation residuals exceeded .10, which represents a slight local fit improvement compared to the original five-factor model with no correlated errors.

Based on the results just described the five-factor CFA model in Figure 23 was retained but with four error correlations (see Figure 24). Reported in Table 10 are estimates of pattern coefficients and error variances for the final five-factor CFA model with four error correlations.

Estimates of factor variances, covariances, and of the four error covariances for the final five-factor CFA measurement model are listed in Table 11. Equally important, the reliability values of factors by coefficients alpha and omega, as well as the average variance extracted (AVE), and the square root of the AVE are reported in Table 12.

The alpha and omega reliability values indicate acceptable (.683) to excellent (.916) internal consistency for latent constructs (see Table 12). Of greater interest, the AVE measure suggests acceptable convergent validity for the trait anxiety (.756), cognitive flexibility (.603), cognitive avoidance (.642), and dispositional mindfulness (.718) factors. However, the decentering (.429) latent construct showed a poor convergent validity as it explained less than 50% of the variance in its indicator variables. Furthermore, the square root of the AVE surpassed the higher inter-construct correlation (r=-.775) in absolute value for trait anxiety (.869), cognitive flexibility (.777), cognitive avoidance (.801), and dispositional mindfulness (.847), which suggests acceptable discriminant validity for these constructs. In contrasts, the decentering (.655) latent construct showed a poor discriminant validity. Although the decentering latent construct demonstrated convergent and divergent validity problems, we did not remove this factor because the global fit indices of the measurement model with four correlated errors were generally favorable, CFI=.955, RMSEA=.069, 90% *CI* [.048, .088], SRMR=.058. The four error correlations were -.826, .319, .387, and .337, respectively (see Table 11). Some of these correlations does not seem large, but their presence helps to diminish local fit problems in the standard five-factor CFA model without these parameters.

Table 10. *Maximum likelihood estimates of pattern coefficients and residuals for the final five-factor measurement model of trait anxiety and cognitive control*

	Pattern coefficients				Error variances			
	Unstandardized		Standardized		Unstandardized		Standardized	
Indicator	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Trait anxiety								
STAI-1	1.000	-	.874	.027	4.453	.865	.236	.047
STAI-2	.964	.045	.824	.037	6.295	1.126	.320	.061
STAI-3	.999	.062	.913	.023	2.877	.679	.167	.043
Cognitive flexibility								
CFI-1	1.000	-	.855	.034	4.125	.884	.269	.059
CFI-2	.766	.057	.824	.036	3.105	.595	.321	.059
CFI-3	.496	.068	.552	.064	6.265	.794	.695	.071
Cognitive avoidance								
CAQ-1	1.000	-	.800	.073	7.073	2.216	.360	.117
CAQ-2	1.101	.152	.872	.049	4.793	1.755	.240	.085
CAQ-3	.970	.147	.732	.050	10.221	1.513	.464	.073
Decentering								
EQ-1	1.000	-	.651	.074	3.105	.560	.576	.096
EQ-2	1.283	.206	.652	.055	5.092	.627	.575	.072
EQ-3	.846	.147	.669	.063	2.016	.270	.552	.084
Dispositional mindfulness								
MAAS-1	1.000	-	.825	.031	10.460	1.571	.319	.052
MAAS-2	1.082	.088	.891	.029	6.774	1.536	.206	.051
MAAS-3	.834	.073	.813	.034	7.933	1.087	.338	.055

Note. Est.=Estimate. SE=Robust standard error. The standardized solution is completely standardized. The results were computed using the *lavaan* package in R.

Table 11. *Maximum likelihood estimates of factor variances, covariances, and error covariances for the final five-factor measurement model of trait anxiety and cognitive control*

Parameter	Unstandardized Est.	Unstandardized SE	Standardized Est.	Standardized SE
Factor variances and covariances				
Trait anxiety	14.391	1.796	1.000	-
Cognitive flexibility	11.188	1.717	1.000	-
Cognitive avoidance	12.564	3.173	1.000	-
Decentering	2.286	.627	1.000	-
Dispositional mindfulness	22.300	3.250	1.000	-
Trait anxiety ↔ Cognitive flexibility	-9.840	1.418	-.775	.048
Trait anxiety ↔ Cognitive avoidance	8.428	1.601	.627	.062
Trait anxiety ↔ Decentering	-4.101	.736	-.715	.062
Trait anxiety ↔ Dispositional mindfulness	-8.408	1.727	-.469	.080
Cognitive flexibility ↔ Cognitive avoidance	-7.094	1.332	-.598	.066
Cognitive flexibility ↔ Decentering	3.182	.657	.629	.070
Cognitive flexibility ↔ Dispositional mindfulness	4.620	1.736	.292	.103
Cognitive avoidance ↔ Decentering	-2.259	.605	-.421	.087
Cognitive avoidance ↔ Dispositional mindfulness	-6.703	1.798	-.400	.084
Decentering ↔ Dispositional mindfulness	2.513	.775	.352	.093
Error covariances				
CAQ-1 ↔ CAQ-2	-4.808	1.405	-.826	.425
STAI-1 ↔ STAI-2	1.690	.779	.319	.112
STAI-3 ↔ CAQ-3	2.100	.570	.387	.095
CFI-1 ↔ EQ-2	1.544	.577	.337	.109

Note. Est.=Estimate. SE=Robust standard error. The standardized solution is completely standardized. The results were computed using the *lavaan* package in R.

Table 12. *Reliability values for the final five-factor measurement model of trait anxiety and cognitive control*

Latent construct	Alpha	Omega	Average variance extracted (AVE)	Square root (AVE)
Trait anxiety	.916	.881	.756	.869
Cognitive flexibility	.785	.809	.603	.777
Cognitive avoidance	.800	.905	.642	.801
Decentering	.683	.687	.429	.655
Dispositional mindfulness	.878	.883	.718	.847

Note. The results were computed using the *lavaan* package in R.

The analyses described next concern the second step of two-step modeling, specifically, the testing of partially latent structural regression models, with the measurement part established in the first step but with alternative versions of structural models. The first model analyzed is a partially latent parallel mediation model of trait anxiety and cognitive control. Values of selected fit statistics are reported in Table 7. Presented in Figure 25 and Table 13 are parameter estimates for the partially latent parallel mediation model. All unstandardized and standardized direct effects of trait anxiety towards mediating variables (e.g., cognitive avoidance, cognitive flexibility, decentering, and dispositional mindfulness) were significant at .05 level. However, the unstandardized and standardized direct effects of trait anxiety and the mediator variables towards the outcome variables (e.g., task-switching cost and reversal learning) were not statistically significant. This implies that trait anxiety did not have a direct or indirect effect on the outcome variables and, therefore, none of the hypotheses of the study were supported (see

Table 13). Furthermore, a negative nonsignificant association was found between task-switching cost and reversal learning, r=-.059, p=.420.

Alternative theoretical models were then tested to evaluate whether fit might be improved by restricting the paths from the mediator variables towards the outcome variables (Direct effects model [Table 7 and Figure 26]) or by restricting the paths from trait anxiety towards the outcome variables (Indirect effects model [Table 7 and Figure 27]). There were no differences in global fit between the parallel mediation model and the direct effects (χ^2_D=6.01, df_D=6, p=.423) and indirect effects (χ^2_D=2.70, df_D=2, p=.259) alternative models. Regarding local fit, the parallel mediation, direct effects, and indirect effects models had seventeen, twenty-one, and eighteen absolute correlation residuals above .10, respectively. We chose to retain the partially latent parallel mediation model considering that it has slightly fewer local fit problems and has more theoretical support for the hypothesized linkages between variables compared to both alternative models.

We used the *semTools* package (Jorgensen et al., 2021) and the *findRMSEApower* function to estimate power for the final parallel mediation model, given N=149, df_M=104, α=.05. Assuming ε_1=.08 for the test of the close-fit hypothesis ($\varepsilon_0 \leq .05$), power is .871. Now assuming ε_1=.01 for the test of the not-close-fit hypothesis ($\varepsilon_0 \geq .05$), power is .698. These results indicate that the probability of rejecting a false model is good, while the probability of detecting a correct model is acceptable. Although the sample size for this analysis is not large, there are sufficient model degrees of freedom to reduce the negative impact of small samples on statistical power.

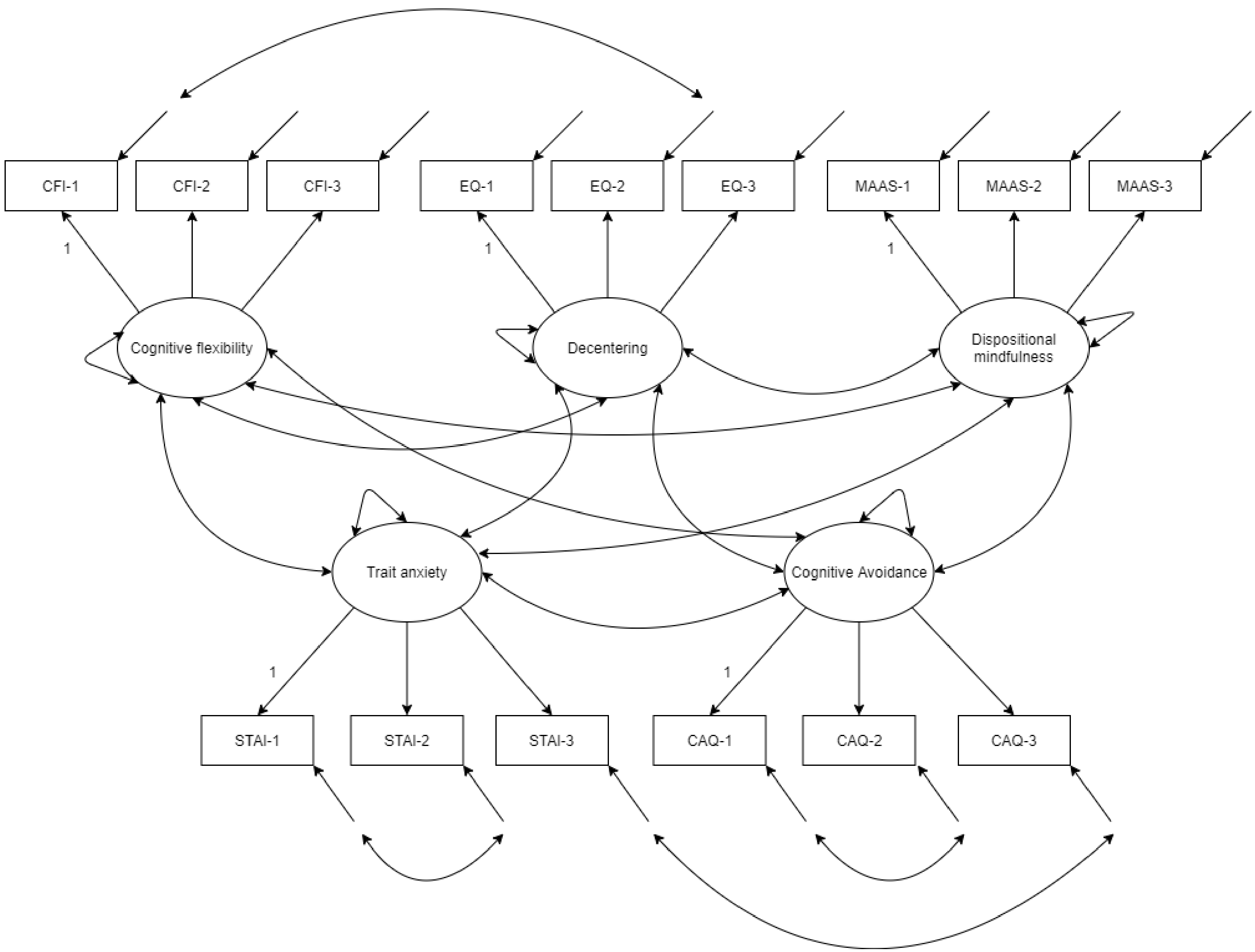

Figure 24. *Final five-factor measurement component in a partially structural regression model of trait anxiety and cognitive control with compact symbolism for indicator error terms*

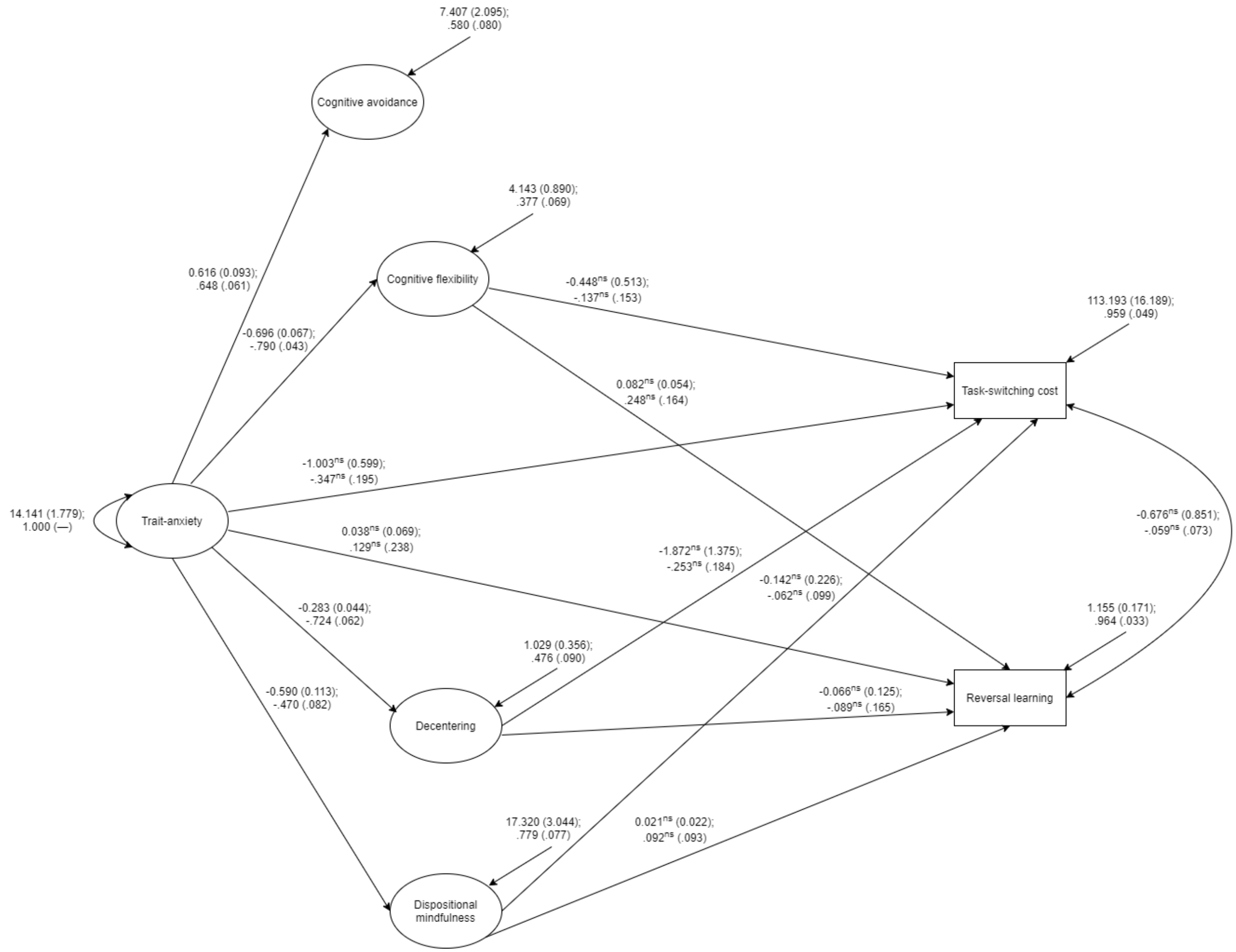

Figure 25. *Structural component in a partially latent parallel mediation model of trait anxiety and cognitive control with compact symbolism for disturbances. Estimates in the top row are unstandardized (robust standard error); estimates in the bottom row are standardized (robust standard error). Standardized estimates are from a completely standardized solution. All estimates are statistically significant at the .05 level except for those designated "ns", which means not significant.* The results were computed using the *lavaan* package in R.

Table 13. *Maximum likelihood estimates for the structural component in a partially latent parallel mediation model of trait anxiety and cognitive control*

Parameter	Unstandardized	SE	Standardized	SE
	Direct effects			
Trait anxiety → Cognitive avoidance	0.616	0.093	.648	.061
Trait anxiety → Cognitive flexibility	-0.696	0.067	-.790	.043
Trait anxiety → Decentering	-0.283	0.044	-.724	.062
Trait anxiety → Dispositional mindfulness	-0.590	0.113	-.470	.082
Trait anxiety → Task-switching cost	-1.003^{ns}	0.599	-.347^{ns}	.195
Cognitive flexibility → Task-switching cost	-0.448^{ns}	0.513	-.137^{ns}	.153
Decentering → Task-switching cost	-1.872^{ns}	1.375	-.253^{ns}	.184
Dispositional mindfulness → Task switching cost	-0.142^{ns}	0.226	-.062^{ns}	.099
Trait anxiety → Reversal learning	0.038^{ns}	0.069	.129^{ns}	.238
Cognitive flexibility → Reversal learning	0.082^{ns}	0.054	.248^{ns}	.164
Decentering → Reversal learning	-0.066^{ns}	0.125	-.089^{ns}	.165
Dispositional mindfulness → Reversal learning	0.021^{ns}	0.022	.092^{ns}	.093
	Indirect effects			
Trait anxiety → Cognitive flexibility → Task-switching cost	0.312^{ns}	0.357	.108^{ns}	0.120
Trait anxiety → Decentering → Task-switching cost	0.529^{ns}	0.409	.183^{ns}	0.137
Trait anxiety → Dispositional mindfulness → Task-switching cost	0.084^{ns}	0.134	.029^{ns}	0.047
Trait anxiety → Cognitive flexibility → Reversal learning	-0.057^{ns}	0.038	-.196^{ns}	0.129
Trait anxiety → Decentering → Reversal learning	0.019^{ns}	0.035	.064^{ns}	0.120
Trait anxiety → Dispositional mindfulness → Reversal learning	-0.013^{ns}	0.013	-.043^{ns}	0.044

Parameter	Unstandardized	SE	Standardized	SE
	<u>Disturbance variances and covariances</u>			
Cognitive avoidance	7.407	2.095	.580	.080
Cognitive flexibility	4.143	0.890	.377	.069
Decentering	1.029	0.356	.476	.090
Dispositional mindfulness	17.320	3.044	.779	.077
Task-switching cost	113.193	16.189	.959	.049
Reversal learning	1.155	0.171	.964	.033
Task-switching cost Reversal learning	-0.676^{ns}	0.851	-.059^{ns}	.073

Note. SE=Robust standard error. Standardized estimates for disturbance variances are proportions of unexplained variance. All estimates are statistically significant at the .05 level except for those designated “ns”, which means not significant. The standardized solution is completely standardized. Trait anxiety does not have disturbance variance because it is an exogenous latent variable. The results were computed using the *lavaan* package in R.

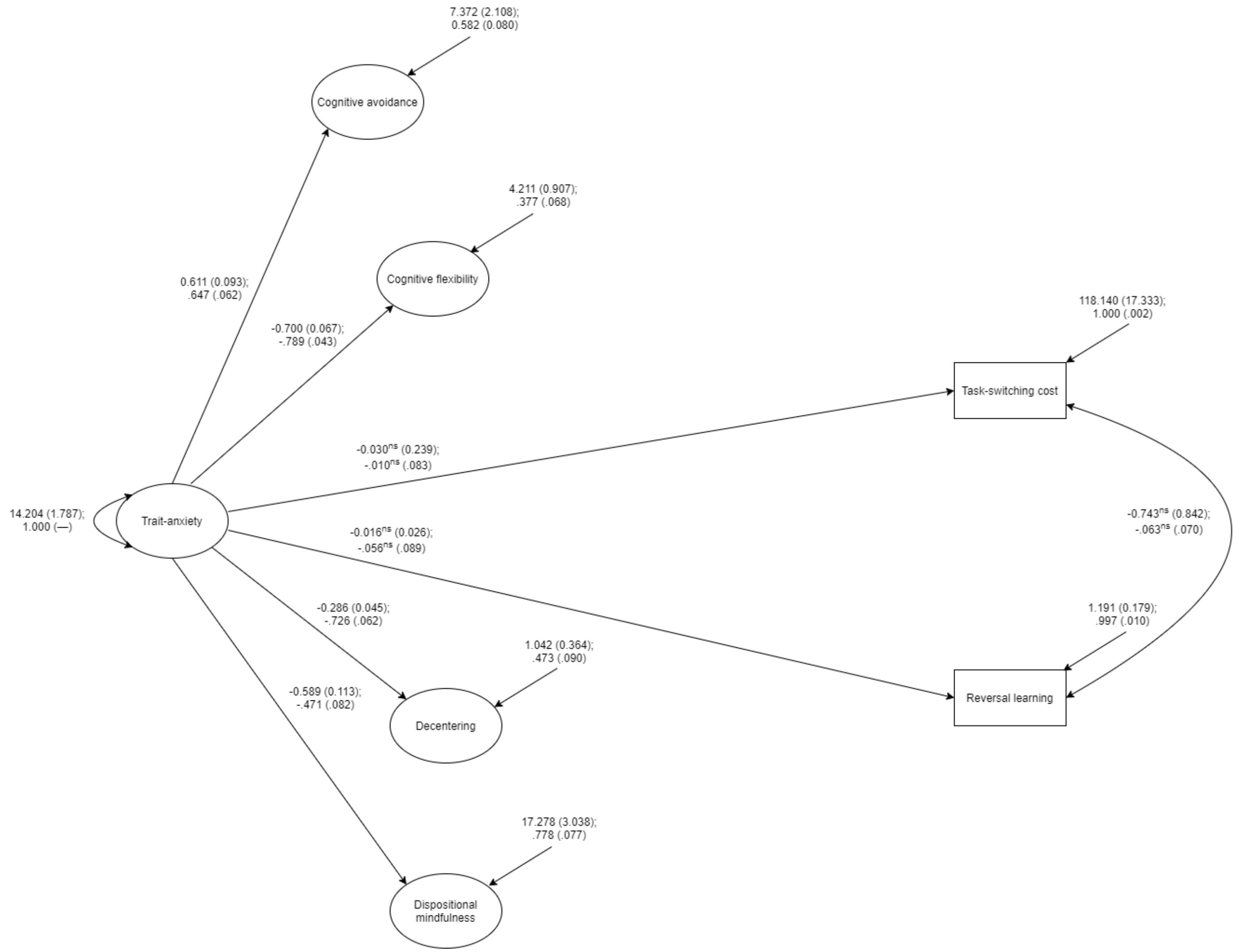

Figure 26. *Structural component in a partially latent direct effects model of trait anxiety and cognitive control with compact symbolism for disturbances. Estimates in the top row are unstandardized (robust standard error); estimates in the bottom row are standardized (robust standard error). Standardized estimates are from a completely standardized solution. All estimates are statistically significant at the .05 level except for those designated "ns", which means not significant.* The results were computed using the *lavaan* package in R.

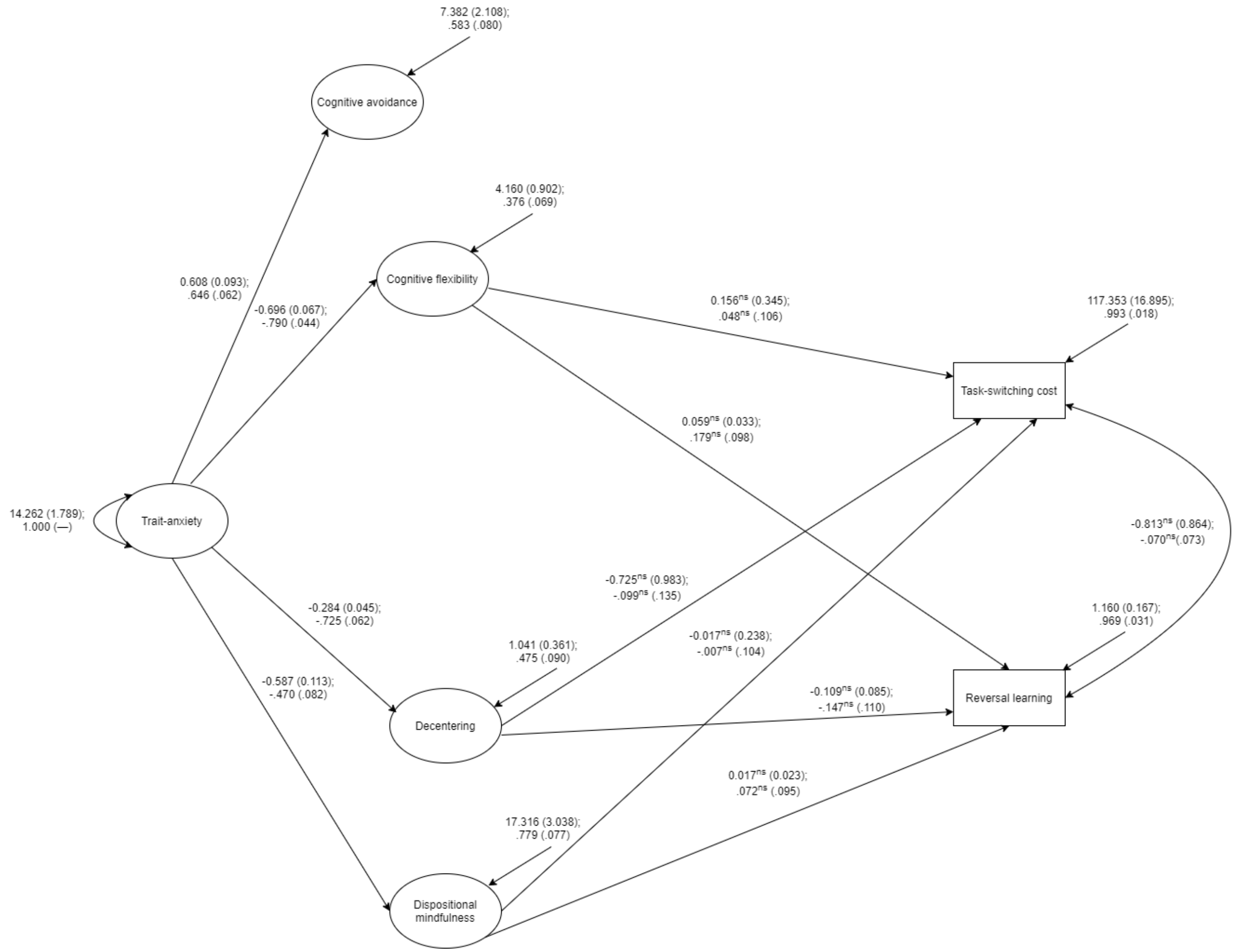

Figure 27. *Structural component in a partially latent indirect effects model of trait anxiety and cognitive control with compact symbolism for disturbances. Estimates in the top row are unstandardized (robust standard error); estimates in the bottom row are standardized (robust standard error). Standardized estimates are from a completely standardized solution. All estimates are statistically significant at the .05 level except for those designated "ns", which means not significant.* The results were computed using the *lavaan* package in R.

Discussion

The purpose of the present study was to contribute filling a gap in the scientific literature regarding the need to develop and test comprehensive models of the relation between trait anxiety and cognitive control. We conducted a partially latent parallel mediation model using a two-step structural equation modeling approach to evaluate the direct and indirect paths that connect trait anxiety, cognitive avoidance, cognitive flexibility, decentering, dispositional mindfulness, task switching cost, and reversal learning. Although we found significant direct effects of trait anxiety towards the mediating variables (e.g., cognitive avoidance, cognitive flexibility, decentering, and dispositional mindfulness), the direct effects of trait anxiety and the mediating variables towards the outcome variables (e.g., task switching cost and reversal learning) were not significant. Consequently, contrary to expectations, none of the primary parallel mediation hypotheses of the study were supported.

The study findings lead us to focus on two main topics of discussion. First, there are some processes associated with emotional regulation that are interrelated, but that did not demonstrate a significant relation with purely cognitive aspects. This implies that Spanish-speaking young adults did not have a generalized cognitive problem because the cognitive computerized tasks did not show any significant relation with the personality characteristic variables. In contrast, the observed linkages among variables show that the participant's problems tend to be affective in nature. Therefore, we delineated similarities and differences between the observed relations in each of the twelve direct paths of the partially latent parallel mediation model of trait anxiety and cognitive control (see Figure 25 and Table 13) and the work of others. Second, what distinguishes this investigation from several works in the literature is the complexity and transparency of the statistical analyses conducted. We follow state of the art journal article reporting standards (Appelbaum et al., 2018). For this reason, we performed a critical analysis of poor practices in published studies that examined the relation between the personality characteristics associated with emotional regulation and the purely cognitive aspects of task-switching cost and reversal learning. We argue that reporting poor-quality psychological research reproduce unreliable findings that will not be replicated in future studies. Hence, we describe alternative best practice approaches that previous authors could have used to produce higher quality research papers.

Next, we delineate the similarities and differences between our results and the work of others.

Similarities and differences between our results and the work of others

We compared each of the twelve direct paths of the partially latent parallel mediation model of trait anxiety and cognitive control (see Figure 25 and Table 13) with previous works in the literature. Specifically, we compared our results with the work of others on the twelve direct paths outlined in Table 14.

Table 14. *Overview of the twelve direct paths of the partially latent parallel mediation model*

Path #	Direct paths
1	Trait anxiety → Cognitive avoidance
2	Trait anxiety → Cognitive flexibility
3	Trait anxiety → Decentering
4	Trait anxiety → Dispositional mindfulness
5	Trait anxiety → Task-switching cost
6	Trait anxiety → Reversal learning
7	Cognitive flexibility → Task-switching cost
8	Cognitive flexibility → Reversal learning
9	Decentering → Task-switching cost
10	Decentering → Reversal learning
11	Dispositional mindfulness → Task-switching cost
12	Dispositional mindfulness → Reversal learning

Path #1. Direct effect of trait anxiety on cognitive avoidance

The direct effect of trait anxiety on cognitive avoidance was positive and significant, as hypothesized. Equally important, the magnitude of the effect was large with trait anxiety explaining 42% of the variability in cognitive avoidance. In other words, Spanish-speaking young adults with higher trait anxiety symptoms are more likely to frequently use cognitive avoidance strategies compared to their counterparts with lower anxiety levels. This finding reflects a problem of an affective nature in the participants of the study because cognitive avoidance is widely recognized in the literature as a maladaptive emotional regulation strategy (Sagui-Henson, 2017). For example, using thought suppression techniques to inhibit the emotional processing of feared stimuli can seem beneficial in the short-term but will most likely result in experiencing a rebound effect in the long-term (Sexton & Dugas, 2008).

Similarly, Williams (2015) found positive and significant correlations between cognitive avoidance and various measures of statistical anxiety. Although these correlations were statistically significant, the magnitude or practical importance of these associations was small, as the variables shared less than 9% of the variability in their scores. This indicates that the direction and significance of the relation between cognitive avoidance and anxiety remains constant in participants with different types of anxiety. However, the practical importance of these relations, evaluated with the coefficient of determination (R^2) as an effect size index of the proportion of variance explained, seems to vary greatly depending on the specific measures of cognitive avoidance and anxiety used in different studies.

The main point of contrast between our investigation and the work of others is in assigning an active role to anxiety in predicting cognitive avoidance. For example, Mahoney and coworkers (2018) proposed that cognitive avoidance exerts a significant direct effect on generalized anxiety disorder symptoms. That is, these authors assigned an active predictor role to cognitive avoidance as a factor that contributes to generalized anxiety disorder symptom severity. In the same way, Spinhoven and colleagues (2017) concluded that cognitive avoidance strategies are long-term predictors of anxiety disorders. Notwithstanding, we propose an alternative approach in which participants with higher trait anxiety are more likely to use cognitive avoidance strategies. This is because cognitive avoidance strategies such as thought suppression and distraction are commonly used to inhibit emotional processing of threatening stimuli and individuals with high trait anxiety are more likely to experience negative emotions across many situations (Gidron, 2013; Sexton & Dugas, 2008).

Path #2. Direct effect of trait anxiety on cognitive flexibility

We observed a negative direct effect of trait anxiety on cognitive flexibility. Moreover, the practical importance of the effect was large with trait anxiety explaining 62% of the variability in cognitive flexibility. Thus, the higher the trait anxiety levels of the Spanish-speaking young adults, the lower their self-reported cognitive flexibility abilities. This finding suggests that there is motive for concern from an emotional regulation perspective. This is because participants with lower cognitive flexibility capabilities are less likely to adequately respond to changing circumstances and to perceive themselves as capable of facing and overcoming challenging tasks (Dennis & Vander-Wal, 2010).

Likewise, Johnco and collaborators (2015) found that participants with comorbid anxiety and depression had lower cognitive flexibility capabilities than nonclinical controls. These researchers highlighted the practical implications of this affective problem. Specifically, their results show that the clinical group was worse at benefiting from a cognitive-behavioral therapy aimed at teaching people to identify and dispute maladaptive thoughts and this is partially related due to having poor cognitive flexibility skills (Johnco et al., 2015). Correspondingly, Johnco and coworkers (2014) had previously found that individuals with lower cognitive flexibility abilities were less successful in effectively using cognitive restructuring strategies to reduce emotional distress.

In general, it is common to find a negative and significant relation between anxiety and cognitive flexibility in the literature. Furthermore, all the studies we examined were consistent in assigning a predictive role to anxiety in reducing cognitive flexibility abilities. However, contrary to our two-step structural equation modeling approach to examine the direct effect of trait anxiety on cognitive flexibility, some of the empirical articles reported overly simplistic statistical analyses to tests their hypotheses. For example, Simon and Verboon (2016) used the traditional Pearson correlation to examine the association between psychological inflexibility and several measures of anxiety without addressing the distributional assumption of normality. Accordingly, there is a need for more empirical work using innovative data analysis techniques to evaluate the association between anxiety and cognitive flexibility.

Path #3. Direct effect of trait anxiety on decentering

As predicted, the direct effect of trait anxiety on decentering was negative and significant. Additionally, the magnitude of the effect was large with trait anxiety explaining 52% of the variability in decentering. Therefore, Spanish-speaking young adults with higher trait anxiety levels tend to report lower decentering capabilities. This finding provides additional evidence on the affective problems of the participants in this study. Specifically, people with lower decentering abilities are less likely to approach situations using an openminded thinking approach. Consequently, trait anxiety should be considered as a risk factor that hinders the use adaptive emotional regulation strategies and that facilitates the use of maladaptive cognitive styles such as centered thinking.

Similarly, O'Toole and coworkers (2019) found a negative association between decentering and trait anxiety. The correlation between decentering and trait anxiety was statistically significant and the magnitude of the effect was of moderate importance as the variables shared 13% of the variability in their scores. However, this effect size was rather small compared to the effect size found in our study (52%). At first, we did not expect to find such a big difference in in the proportion of shared variability among variables. This is because O'Toole and colleagues (2019) used the same questionnaire as we did to measure decentering (Experiences Questionnaire; Fresco et al., 2007) and a shorter 7-item version of the State-Trait Anxiety Inventory-Trait (Spielberger et al., 1983) to measure trait anxiety. However, this distinct pattern of results could be explained by the methodological differences in the research designs (e.g., clinical vs nonclinical sample, sample size).

As with cognitive avoidance, the main point of contrast between our study and previous works in the literature is the assignment of an active role to anxiety in the prediction of decentering. There is a consensus in the reviewed empirical articles proposing that improvement in decentering temporally precedes reduction in several anxiety-related outcome measures (Hayes-Skelton & Graham, 2013; Hayes-Skelton & Lee, 2018; Hayes-Skelton & Lee, 2019; Hayes-Skelton et al., 2015). Hence, these authors assigned an active predictor role to decentering as a mechanism of action that decreases anxiety symptoms both in cross-sectional and longitudinal studies. In contrast, we propose that participants with higher trait anxiety tend to display lower decentering abilities as a direct consequence of the adverse effects of anxiety on emotional regulation.

Path #4. Direct effect of trait anxiety on dispositional mindfulness

As expected, the direct effect of trait anxiety on dispositional mindfulness was negative and significant. Equally important, the practical importance of the effect was moderate with trait anxiety explaining 22% of the variability in dispositional mindfulness. In other words, Spanish-speaking young adults with higher trait anxiety symptoms tend to demonstrate lower dispositional mindfulness self-reported scores compared to their counterparts with lower anxiety. This finding further evidences the affective problems in the participants of this study. This is because participants with lower dispositional mindfulness tendencies are less likely to remain in mindful states over time, which could lead to increased levels of emotional distress (Boettcher et al., 2014; Brown et al., 2007; Kabat-Zinn, 2003; Sunquist et al., 2018).

In the same way, Cernetic's (2015) findings demonstrate evidence of a moderate to large negative correlation between mindfulness and anxiety. Cernetic (2015) proposed three possible explanations of the negative association between these variables: 1) the awareness dimension of mindfulness might reduce anxiety by attenuating the automaticity of an individual reacting to threatening stimuli; 2) a decentered approach could lead to a more objective perspective of an individual towards their inner experience; and 3) the acceptance dimension of mindfulness might reduce anxiety through creating opportunities for internal self-exposure of an individual to feared stimuli and thus lowering the need for thought suppression and other cognitive avoidance strategies. Although the scope of Cernetic's (2015) study was correlational, the proposed interpretations assume that there is a direct or indirect effect of dispositional mindfulness on anxiety.

Like Cernetic (2015), the current consensus in the literature considers that dispositional mindfulness is the predictor variable that causally explains the reduction of anxiety symptoms, by exerting positive effects in emotional regulation (Freudenthaler et al., 2017; Ostafin et al., 2014; Parmentier et al., 2019). In contrast, we assigned an active predictor role to trait anxiety in causally explaining the changes in dispositional mindfulness, since the proposed explanations by Cernetic (2015) could be interpreted the other way around: 1) an increase in anxiety could heighten the automaticity of an individual reacting to threatening stimuli, which might lower the awareness dimension of mindfulness; 2) an increase in anxiety could lead an individual to use a maladaptive centered approach towards interpreting their inner experiences; and 3) an increase in anxiety could facilitate the use of thought suppression and other cognitive avoidance strategies that might lower the acceptance dimension of mindfulness. Hence, contrary to the current consensus, trait anxiety could be considered as the predictor variable that causally explains the reduction of dispositional mindfulness, by exerting negative effects in emotional regulation. Equally important, future studies could use complex statistical models to analyze the bidirectional effects that trait anxiety and dispositional mindfulness could be simultaneously exerting on each other.

Path #5. Direct effect of trait anxiety on task-switching cost

Contrary to our expectations, the direct effect of trait anxiety on task-switching cost was not statistically significant. Therefore, the performance of the Spanish-speaking young adults in the task-switching alternating task was not affected by trait anxiety level, while controlling for the effects of cognitive flexibility, decentering, and dispositional mindfulness. This finding shows that the participants did not have a generalized cognitive problem since there was no relation between the purely cognitive aspect of the task-switching cost outcome and the personality characteristic measures associated to emotional regulation. Specifically, participants with varying levels of trait anxiety demonstrated an equal loss in efficiency associated with redirecting their attention from the task-repeat and task-switch conditions, while considering the effects of cognitive flexibility, decentering, and dispositional mindfulness.

Similarly, Gul and Humphreys (2014) designed a switching experiment with Rogers and Monsell's (1995) alternating-run task switching paradigm where the task changed every two trials. The cognitive computerized paradigm was designed with 32 facial photographs which presented happy and angry expressions. In contrast to our results, Gul and Humphreys (2014) found a positive and significant direct effect between anxiety scores and task-switching cost. In other words, participants with greater anxiety levels were more likely to display a higher switch-cost outcome compared to their counterparts with lower anxiety levels. It is important to acknowledge, however, that contrary to Gul and Humphreys (2014), we designed an exact replica of Rogers and Monsell's (1995) paradigm which consisted of neutral stimuli.

Nevertheless, Eysenck and coworker's (2007) attentional control theory proposes that anxious individuals perform worse on tasks involving the shifting function whether the situation is negative emotional or neutral. For example, Ansari and colleagues (2008) designed a mixed antisaccade paradigm, in which participants performed single-task and mixed-task versions of the paradigm. Contrary to the patterns of results reported in the alternating-run task switching paradigm, it was found that anxiety impaired the efficient shifting of attentional resources to task demands in the absence of negative affective stimuli (Ansari et al., 2008). Similarly, Gustavson and coworkers (2018) examined the relation between trait anxiety and task-switching cost in an emotionally neutral situation. These authors found that the negative effect of trait anxiety on switch cost tend to be observed only when participants must switch away from an effortfully established task set (Gustavson et al., 2018).

After comparing our nonsignificant effect of trait anxiety on task-switching cost with previous works, we propose that simple cognitive tasks such as Rogers and Monsell's (1995) paradigm require using negative emotional stimuli to find a significant association between variables. That is, we suggest that the combination of anxiety and negative emotional stimuli is necessary to find a significant effect of trait anxiety on task-switching cost in a simple task-switching paradigm. This is because anxiety is related with heightened amygdala activation and the attenuated recruitment of prefrontal areas involved in the regulation of attentional resources, and anxious individuals are more likely to present an attentional bias for threat-related stimuli (Bar-Haim, et al., 2007; Bishop, 2007). However, the more complicated the task-switching paradigm, the greater the adverse effect of anxiety on top-down attentional control, which can lead to a significant effect of trait anxiety on switch cost in the absence of negative affective stimuli.

Path #6. Direct effect of trait anxiety on reversal learning

Contrary to hypothesized, the direct effect of trait anxiety on reversal learning did not reach statistical significance. Thus, the performance of the Spanish-speaking young adults in the go/no-go reversal learning task suggest that these participants were not affected by trait anxiety level, while adjusting for the effects of cognitive flexibility, decentering, and dispositional mindfulness. This finding further demonstrates that the participants did not have a generalized cognitive problem since there was no association between the processes associated to emotional regulation and the specific cognitive aspect of reversal learning. This indicates that participants with distinct levels of trait anxiety show an equal ability to improve discrimination of go/no-go stimuli during the recovery phase, while controlling for the effects of cognitive flexibility, decentering, and dispositional mindfulness.

In contrast with our results, Wilson and collaborators (2018) found a significant and negative effect of trait anxiety on reversal learning. Observing a distinct pattern from Wilson et al (2018) was unexpected, since we designed our cognitive computerized paradigm through modifying the cognitive experiment developed by Wilson and coworkers (2018). Specifically, we used images (e.g., polygonal ["go"] vs non-polygonal ["no-go"]) as stimuli instead of numbers (e.g., 16, 11, 97, 78 ["go"] vs 86, 17, 83, 42 ["no-go"]). However, in retrospective, we believe that our task was too simple since the overall proportion of hits (e.g., correctly making a "go" response in a "go task") in our sample was .84, while Wilson and coauthors (2018) participant's proportion of hits were below .70. It is likely that our cognitive computerized task was simpler, and it may not have caused sufficient stress among participants which are prone to anxiety.

Comparable to the task-switching paradigm, we propose that simple go/no-go tasks might require using negative emotional stimuli to find a significant effect of trait anxiety on reversal learning. This is because the intrinsic negative influence of trait anxiety on the shifting and inhibition executive functions (Ansari et al., Eysenck et al., 2007; Gustavson et al., 2018) might heighten with task complexity. Hence, if the task is too simple, the negative influence of anxiety on top-down processing is less likely to reach statistical significance and vice versa. Additionally, using negative emotional stimuli in a more complex go/no-go task could lead to strengthening the practical importance of the negative effect of trait anxiety on reversal learning. We understand that a lack of understanding on how negative stimuli may influence the go/no-go reversal learning task results is a gap in the literature that should be addressed in future studies.

Path #7. Direct effect of cognitive flexibility on task-switching cost

Contrary to our predictions, the direct effect of cognitive flexibility on task-switching cost was not statistically significant. Consequently, the performance of the Spanish-speaking young adults in the task-switching alternating task was not influenced by the level of cognitive flexibility, while considering the effects of trait anxiety, decentering, and dispositional mindfulness. This finding provides additional evidence that participant's emotional regulation problems did not generalize to the purely cognitive aspect of the task-switching cost outcome.

Similarly, Liu and coworkers (2015) examined the effect of cognitive flexibility on task-switching cost. These authors used a sample of 52 low proficiency Chinese (L1)-English (L2) bilinguals, which were assigned either to a low or high cognitive flexibility group based on their performances in the Wisconsin Card Sorting Test (Grant & Berg, 1948; Heaton et al., 1993). The switch cost measure was assessed with the Simon switch task, which consists of pressing a button congruent (e.g., when the arrow was red) or incongruent (e.g., when the arrow was blue) to the pointing direction of an arrow. In contrast with our results, Liu and collaborator's (2015) found that switch cost for the congruent and incongruent conditions were symmetrical in the high cognitive flexibility group, whereas the low cognitive flexibility group demonstrated larger switch costs for congruent than incongruent trials. These results replicated Gajewski and colleague's (2010) findings, indicating that cognitive flexibility can modulate task switch costs.

We identified two important methodological differences between Liu and coworker's (2015) research and our investigation that could play a role in the distinct patterns of results found. First, we measured cognitive flexibility using a self-report instrument (Cognitive Flexibility Inventory; Dennis & Vander-Wal, 2010), while Liu and colleagues (2015) used a neuropsychological test (Wisconsin Card Sorting Test; Grant & Berg, 1948; Heaton et al., 1993).

Accordingly, it seems that using a performance measure of cognitive flexibility is more likely to be significantly related with task-switching cost, as opposed to using a self-report instrument. Second, the task-switching alternating paradigm measures the shifting aspect of executive function by examining the cost a predictable switch between task-repeat and task-switch conditions. However, the Simon switch task measures both the shifting and inhibition aspects of executive function because the direction of arrows is a strong interference for incongruent (e.g., when the arrow was blue) trials. For that reason, the Simon switch task seems to be more complex than the task-switching alternating paradigm.

After comparing our results with work of others, we propose that caution is needed when generalizing findings that address the direct effect of cognitive flexibility on task-switching cost. The interpretation of results must strictly consider the way in which the constructs of cognitive flexibility and task-switching cost were operationalized. In our study, there seems to be no relation between participant's tendencies towards perceiving difficult situations as controllable and their scores on the task-switching alternating task. However, future studies could benefit from measuring distinct aspects of cognitive flexibility using several data collection strategies (e.g., self-report instrument, neuropsychological test) to identify which dimensions of cognitive flexibility are significantly related to performance measures of switch cost.

Path #8. Direct effect of cognitive flexibility on reversal learning

Contrary to hypothesized, the direct effect of cognitive flexibility on reversal learning did not reach statistical significance. Therefore, the performance of the Spanish-speaking young adults in the go/no-go reversal learning task was not affected by cognitive flexibility level, while controlling for the effects of trait anxiety, decentering, and dispositional mindfulness. This finding provides additional evidence that the participants did not show a generalized cognitive problem, as there was no association between the personality characteristics related with emotional regulation and the specific cognitive function of reversal learning. This indicates that participants with distinct levels of cognitive flexibility show a similar capacity to improve discrimination of go/no-go stimuli during the recovery phase, while considering the effects of trait anxiety, decentering, and dispositional mindfulness.

To the best of our knowledge, no previous study has examined the effect of a self-report measure of cognitive flexibility on a performance measure of reversal learning. Conversely, there was a tendency on the revised studies towards using reversal learning as a standard indicator of cognitive flexibility (Nusbaum et al., 2018; Wilson et al., 2018). In other words, the performance outcome in the reversal learning paradigm tends to be considered as an objective representation of the cognitive flexibility capacity of the individuals. This implies that there is a consensus towards assigning a passive dependent role to cognitive flexibility as reflected by the performance in the reversal learning task.

Considering the above, we understand that our investigation addressed a gap in the literature regarding the need to simultaneously examine two different dimensions of cognitive flexibility. On the one hand, we measured cognitive flexibility as a personality characteristic associated with emotional regulation. On the other hand, we examined the specific cognitive flexibility aspects of inhibition and shifting as measured by the performance in the go/no-go reversal learning task. Our nonsignificant finding could be associated to using a general cognitive flexibility construct (e.g, tendency to perceive difficult situations as controllable) as opposed to using an operational definition that considers the shifting and inhibition aspects of reversal learning. Thus, future works should consider that although all reversal learning studies involve cognitive flexibility, not all cognitive flexibility studies involve reversal learning.

Specifically, evidence from functional neuroimaging studies indicates that human reversal learning engages the lateral orbitofrontal cortex, dorsal anterior cingulate cortex, and right inferior frontal cortex (Ghahremani et al., 2010; Izquierdo et al., 2017; Uddin, 2021).

Path #9. Direct effect of decentering on task-switching cost

Contrary to our predictions, the direct effect of decentering on task-switching cost was not statistically significant. Accordingly, the performance of these Spanish-speaking young adults in the task-switching alternating task was not influenced by the level of decentering, while considering the effects of trait anxiety, cognitive flexibility, and dispositional mindfulness. This finding clearly evidences that the participants did not show a generalized cognitive problem, since there was no relation between the purely cognitive aspect of the task-switching cost outcome and the personality characteristics associated with emotional regulation. It seems that participants with different levels of decentering demonstrated a similar loss in efficiency related with continuously alternating between the task-repeat and task-switch conditions, while controlling for the effects of trait anxiety, cognitive flexibility, and dispositional mindfulness.

Similarly, Kessel and collaborators (2016) examined the association between decentering and the ability to shift attention. These authors used a sample of 55 healthy students who did not suffer from any physical or mental illness. The decentering variable was measured using the German version of the Experiences Questionnaire (Gecht et al., 2014) and the ability to shift attention was measured with the German version of the color word Stroop interference test (Bäumler, 1985). The test evaluated two different task types of increasing difficulty. First, participants had to name the color of control patches, which implies for example naming blue when a blue patch is presented (color patches naming, CPN). Second, participants had to name the incongruent color of color words, for example, naming yellow when the word red was written in yellow ink (interference, INT). The higher the difference between the completion time of both tasks, the higher is the interference and the lower the capacity of shifting attention.

Comparable to our results, Kessel and coworkers (2016) did not find a significant relation between decentering and the ability to shift attention. However, there was an important difference between our cognitive paradigms. Specifically, the task-switching alternating task measures the switching aspect of cognitive control, while the color word Stroop interference test measures both the switch and inhibition executive functions. Hence, although decentering is widely recognized as an adaptive emotional regulation strategy (Bernstein et al., 2015) it does not seem to be directly related to the purely cognitive switching and inhibition processes when using neutral stimuli. However, we suggest that future studies could benefit from examining whether decentering plays a role in diminishing task-switching cost in cognitive paradigms using negative emotional stimuli, through reducing the magnitude of the threat-related attentional bias.

Path #10. Direct effect of decentering on reversal learning

Contrary to our expectations, the direct effect of decentering on reversal learning did not reach statistical significance. Therefore, the performance of the Spanish-speaking young adults in the go/no-go reversal learning task was not affected by decentering level, while adjusting for the effects of trait anxiety, cognitive flexibility, and dispositional mindfulness. This finding further demonstrates that the participant's emotional regulation problems did not generalize towards the purely cognitive aspect of reversal learning. In consequence, participants with distinct levels of decentering tend to show almost identical abilities to improve discrimination of go/no-go stimuli during the recovery phase, while considering the effects of trait anxiety, cognitive flexibility, and dispositional mindfulness.

The literature on the direct effect of decentering on reversal learning is limited, since most investigations tend to consider decentering as an intermediary mechanism through which mindfulness exerts its positive effects on processes associated with emotional regulation (Hayes-Skelton & Graham, 2013; Hayes-Skelton & Lee, 2019). As far as we know, Kessel and collaborators (2016) are the only researchers who have evaluated the association between decentering and executive attention (e.g., shifting and inhibition aspects of the color word Stroop interference test). Moreover, no previous studies have specifically examined the relation between decentering and reversal learning. Thus, Kessel and colleague's (2016) nonsignificant association between decentering and the ability to shift attention is the most similar study with which we can compare our findings.

As discussed above regarding task-switching cost, it seems that decentering plays an important role as a personality characteristic associated with adaptive emotional regulation (Bernstein et al., 2015). However, empirical evidence suggests that decentering does not have a direct linkage with the purely cognitive executive functions of switching and inhibition measured in the go/no-go reversal learning task and the color word Stroop interference effect test. Like Kessel and coauthors (2016) we propose that further investigations should incorporate negative emotional stimuli in their cognitive paradigms when examining the relation between decentering and reversal learning. This would allow to evaluate whether the direct effect of decentering on reversal learning is only reflected in cognitive paradigms that require using a decentered approach to reduce the influence of negative emotional stimuli on performance.

Path #11. Direct effect of dispositional mindfulness on task-switching cost

Contrary to hypothesized, the direct effect of dispositional mindfulness on task-switching cost was not statistically significant. In this way, the performance of the Spanish-speaking young adults in the task-switching alternating task was not influenced by the level of dispositional mindfulness, while considering the effects of trait anxiety, cognitive flexibility, and decentering. This finding provides additional evidence that participant's personality characteristics associated with emotional regulation problems did not exert an effect on the purely cognitive aspect of the task-switching cost outcome. This implies that participants with different levels of dispositional mindfulness showed a similar loss in efficiency related with continuously alternating between the task-repeat and task-switch conditions, while controlling for the effects of trait anxiety, cognitive flexibility, and decentering.

We find that establishing similarities and differences with the work of others is challenging due to the multifaced nature of mindfulness (e.g., trait, state, therapeutic intervention, and meditative practice; Bishop et al., 2004; Shapiro et al., 2006). Equally important, some studies have focused on examining specific aspects of dispositional mindfulness (e.g., observing, describing, acting with awareness, non-judging, and non-reactivity; Baer et al., 2006). Furthermore, although previous studies show the positive effects of mindfulness on processes associated with emotional regulation, mixed results have been found when relating mindfulness to the purely cognitive aspect of task-switching cost (Anderson et al., 2007; Hodgins & Adair, 2010; Jankowski & Holas, 2020; Lebois et al., 2015).

In line with our results, Jankowski and Holas (2020) found that brief mindfulness training did not improved attention shifting in the presence of anxiety (Jankowski & Holas, 2020). This finding is contrary to what was expected based on the attentional control theory (Eysenck et al., 2007). Specifically, the authors hypothesized that brief mindfulness training would improve switching ability indirectly, through reducing the negative influence of anxiety on task-switching cost (Jankowski & Holas, 2020). Like Jankowski and Holas (2020), Anderson and coworker's

(2007) brief mindfulness training study demonstrated a nonsignificant relation between mindfulness and a performance measure of attention shifting. This pattern of findings supports the preliminary hypothesis that attention shifting is not affected by short term mindfulness training (Chiesa et al., 2011).

As far as we know, the only investigation that showed a positive significant relation between mindfulness and switching ability was conducted by Hodgins and Adair (2010). These authors compared the capacity to shift perspectives between expert meditators and nonmeditators through using the ambiguous image perspective-switching task. The results show that meditators identified a greater number of alternative perspectives in multiple perspective images compared to non-meditators (Hodgins & Adair, 2010). According to Chiesa and coworker's (2011) review, Hodgins and Adair's (2010) findings provide preliminary support for the hypothesis that increased switching capacity could result from long term rather than brief mindfulness meditation practices.

Path #12. Direct effect of dispositional mindfulness on reversal learning

Contrary to our expectations, the direct effect of dispositional mindfulness on reversal learning did not reach statistical significance. This indicates that the performance of the Spanish-speaking young adults in the go/no-go reversal learning task was not affected by dispositional mindfulness level, while adjusting for the effects of trait anxiety, cognitive flexibility, and decentering. This finding further shows that the participant's personality characteristics associated with emotional regulation processes did not influence the specific cognitive aspect of reversal learning. Consequently, participants with distinct levels of dispositional mindfulness tend to demonstrate a similar capacity to improve discrimination of go/no-go stimuli during the recovery phase, while considering the effects of trait anxiety, cognitive flexibility, and decentering.

To the best of our knowledge, only one study (Janssen et al., 2018) to date has previously examined the effect of mindfulness on reversal learning. Janssen and collaborators (2018) investigated whether an 8-week mindful eating intervention exerts positive effects on a behavioral measure of reversal learning compared to an active control group of educational cooking in a non-clinical population. Although no significant main effects or interactions were found, a post hoc correlational analysis showed a significant relation between time invested (e.g., in hours) in the intervention program and reversal learning. Specifically, time invested in the mindful eating, but not the educational cooking condition had a significant relation with better reversal learning scores (e.g., lower mean error rate on trials following reversals). Accordingly, contrary to our results, Janssen and coworker's (2018) findings suggest that the greater the time devoted to mindfulness practice, the higher the participant's reversal learning capability.

Due to the limited literature available on the direct effect of dispositional mindfulness on reversal learning, we also compared our results with previous works that addressed the relation between dispositional mindfulness and executive attention (e.g., shifting and inhibition). The current state of the literature employing behavioral measures has been inconsistent, and therefore there has been considerable debate concerning the effect of dispositional mindfulness on executive attention (Joseffson et al., 2014; Lin et al., 2018). Similar to our results, Josefsson and coworkers (2014) found that a short-term mindfulness-based intervention had no effect on a behavioral measure of Stroop interference. Based on their findings, Josefsson and colleagues (2014) went so far as to suggest removing executive attention from the theoretical frameworks of mindfulness (Bishop et al., 2004; Shapiro et al., 2016).

In contrast, Lin and coworkers (2018) found a positive and significant relation between mindfulness and executive attention. These authors argue that Joseffson and coworker's (2014) suggestion to remove executive attention from theoretical models of mindfulness is an unwarranted overgeneralization of their findings, considering that their participants only completed a brief training in mindfulness (Lin et al., 2018). Nevertheless, Lin and coauthors (2018) propose that the mixed results in the literature are most likely due to the heterogeneity of the mindfulness construct and method variance. On the one hand, these authors found that within trait mindfulness, only the acting with awareness facet of the Five-Factor Mindfulness Questionnaire (Baer et al., 2006) was significantly related with improved behavioral and neural measures of executive attention (Lin et al., 2018). On the other hand, the self-report instruments and cognitive paradigms employed to measure mindfulness and executive attention are not homogenous across studies (Lin et al., 2018). Hence, we suggest that future studies would benefit from using more systematic approaches to examine the relation between dispositional mindfulness and executive attention, in general, and reversal learning, in particular.

Summary of the similarities and differences between our results and the work of others

The comparison between our study's results and the work of others can be organized in two main topics: 1) the paths 1 to 4 represent the relations between the personality characteristics associated with emotional regulation processes (e.g., trait anxiety, cognitive avoidance, cognitive flexibility, decentering, and dispositional mindfulness); and 2) the paths 5 to 12 represent the relations between the personality characteristics and the purely cognitive aspects of task-switching cost and reversal learning.

In relation to paths 1 to 4, all the direct effects of trait anxiety on the personality characteristics were statistically significant in the expected directions and thus supported our study's hypotheses. First, we found a positive and significant relation between trait anxiety and cognitive avoidance. Second, we found a negative and significant relation between trait anxiety and cognitive flexibility. Third, we found a negative and significant relation between trait anxiety and decentering. Fourth, we found a negative and significant relation between trait anxiety and dispositional mindfulness. Similarly, the reviewed studies were consistent in finding statistically significant relations between trait anxiety and self-report measures of the personality characteristics (Cernetic, 2015; Johnco et al., 2015; O'Toole et al., 2019; Williams, 2015).

Although the literature on the relation between anxiety and personality characteristics associated with emotional regulation appears to be abundant, we understand that it is actually repetitive. For example, there is a consensus in the literature towards considering anxiety as a passive dependent variable that is causally predicted from cognitive avoidance (Mahoney et al., 2018), decentering (Hayes-Skelton & Graham, 2013; Hayes-Skelton & Lee, 2018; Hayes-Skelton & Lee, 2019; Hayes-Skelton et al., 2015), and dispositional mindfulness (Freudenthaler et al., 2017; Ostafin et al., 2014; Parmentier et al., 2019), respectively. Therefore, we consider that our investigation helps address a gap in the literature towards assigning an active independent variable role to trait anxiety in the prediction of these personality characteristics associated with emotional regulation processes.

The results of paths 1 to 4 clearly demonstrate a problem of an affective nature in our non-clinical sample of Spanish-speaking young adults. In this way, the current investigation has important practical implications for program development and implementation. Considering our findings, it is possible that a training program designed to decrease trait anxiety could serve as an effective intervention for increasing the use of adaptive cognitive strategies (e.g., cognitive flexibility, decentering, and dispositional mindfulness) associated with emotional regulation in the population of Spanish-speaking young adults. Likewise, this intervention could be effective in reducing participant's usage of maladaptive cognitive strategies, such as cognitive avoidance. We suggest that future studies would benefit from empirically testing these preliminary hypotheses.

In relation to paths 5 to 12, none of the direct effects from trait anxiety or the mediating variables (e.g., cognitive flexibility, decentering, and dispositional mindfulness) towards the outcome variables (task-switching cost and reversal learning) were statistically significant. There were mixed results in the literature regarding the relation between personality characteristics associated with emotional regulation and purely cognitive processes, such as switching and inhibition (Gul & Humphreys, 2014; Hodgins & Adair, 2010; Kessel et al., 2016; Josefsson et al., 2014, 2020; Liu et al., 2015; Wilson et al., 2018). In general, the nonsignificant findings were found in studies that used cognitive paradigms consisting of neutral stimuli (Josefsson et al., 2014; Kessel et al., 2016). This could indicate that the influence of personality characteristics on purely cognitive processes could be mostly indirect, through reducing anxiety levels and decreasing attention to threat-related stimuli.

An important difference between our investigation and work of others is related to the robustness and comprehensiveness of the study's statistical models. For instance, we tested a partially latent parallel mediation model using two-step structural equation modelling to examine the direct and indirect effects of trait anxiety on switch cost and reversal learning, through cognitive flexibility, decentering, and dispositional mindfulness. In contrast, analogous to previous works (Ostafin et al., 2014; Mahoney et al., 2018), we could have used three different simple mediation models to independently examine the direct and indirect effects of trait anxiety on the outcome variables, without controlling for the influence of the various covariates.

Accordingly, we understand that our study contributes to filling a gap in the literature regarding the need to develop more complex models that examine the multiple relations between variables.

The results of paths 5 to 12 unanimously evidenced that the emotional regulation problems in the non-clinical sample of Spanish-speaking young adults did not generalize towards the purely cognitive aspects of task switching and reversal learning. Considering the nonsignificant findings of previous studies using cognitive paradigms with neutral stimuli (Josefsson et al., 2014; Kessel et al., 2016), we suggest that this investigation could be replicated using alternative versions of the task-switch alternating and reversal learning tasks with negative emotional stimuli. Likewise, we consider that future studies would benefit from comparing the influence of personality characteristics associated with emotional regulation on behavioral measures of cognitive control when using neutral versus negative emotional stimuli.

In the preceding section we compared our results with work of others without questioning the quality of their findings. Although it is often assumed that published empirical articles have already undergone considerable scrutiny in the peer-review process, we consider that it is necessary to critically evaluate whether these authors implemented best practice approaches when analyzing their data. Considering the contrast between our findings and previous studies regarding performance in computerized cognitive paradigms, we conducted a critical analysis of poor research practices in published empirical articles that are relevant to paths 5 to 12.

Critical analysis of poor research practices in published empirical articles

We intend to follow a logical sequence in our critical analysis of poor research practices in published empirical articles that examined the relation between personality characteristics associated with emotional regulation and performance measures of cognitive control. For this reason, we address the forthcoming points. First, we describe why are journal article reporting standards necessary. Second, we explain how we meet high standards in reporting quantitative psychological research in the current investigation. Third, we expose what are the most common problems in the literature. Fourth, we provide a personal example of a poor research practice. Fifth, we perform a critical analysis of poor research practices in published empirical articles that are relevant to paths 5 to 12.

Why are journal article reporting standards necessary?

It is common knowledge that thousands of psychological empirical articles are published each year and the report of each research project is expected to meet or exceed established quality criteria. The investigators are required to provide sufficient descriptions of the measures and the research design and implementation to make it possible for others to replicate their findings (Appelbaum et al., 2018). However, there have been mixed results in previous studies estimating the reproducibility of psychological science. For example, a large-scale collaborative effort to obtain evidence of the reproducibility of 100 experimental and correlational psychological investigations demonstrated that a large proportion of replicated studies found weaker evidence for the original findings (Aarts et al., 2015).

In line with the above, since the early 2000s, considerable efforts have been made to increase the level of systematicity of psychological science. In 2006, the Publications and Communications Board (P&C Board) of the American Psychological Association (APA) formed the Journal Article Reporting Standards Working Group (JARS Working Group) to attend this issue (Cooper, 2020). Specifically, the P&C Board was interested in learning about reporting standards used in other disciplines related to psychology and adapt them for use by psychologists (Appelbaum et al., 2018). The report of the JARS Working Group was received by the P&C

Board and published in the American Psychologist journal (APA Publications and Communications Board Working Group on Journal Article Reporting Standards, 2008). Equally important, the report and article were included into the sixth edition of the *Publication Manual of the American Psychological Association* (APA, 2010).

In 2015, the P&C Board appointed two working groups. One the one hand, Appelbaum and collaborators (2018) were required to revisit and expand the original 2008 article, which focused exclusively on quantitative research (JARS-Quant Working Group). On the other hand, Levitt and colleagues (2018) were tasked to establish new standards for qualitative investigations (JARS-Qual Working Group). The revised and updated JARS-Quant standards (Appelbaum et al., 2018) and the new JARS-Qual standards (Levitt et al., 2018) were included into the seventh edition of the *Publication Manual of the American Psychological Association* (APA, 2020). These standards are also known as APA Style JARS and represent systematic best practice approaches to conducting high-quality and reproducible psychological research (Cooper, 2020).

How we meet high standards in reporting quantitative psychological research in the current investigation?

We used the revised and updated JARS-Quant standards (Appelbaum et al., 2018) as a checklist while conducting the statistical analyses and reporting the results. This is because we were interested in providing clear and comprehensive information on the statistical methods employed. Regarding preliminary analyses, we followed Appelbaum and collaborator's (2018) recommendations to 1) address the issue of the percentage of missing data, both at the variable (e.g., below 2% missing values for all variables) and participant level (e.g., 85.3% participants had complete data, 14% participants had missing values on one or two variables, and 0.7% participants had missing values on three variables), 2) provide empirical evidence for the causes of data that are missing (e.g., missing completely at random), and 3) describe the methods employed for addressing missing data (e.g., multiple imputation with predictive mean matching).

Equally important, we used Kline's (2016) best practice approach to comprehensively assess the distributional assumption of multivariate normality. First, we identified and excluded one participant (Id #20) who met the criteria to be a multivariate outlier based on the Mahalanobis distance. Second, we assessed univariate and multivariate normality numerically using measures of skewness and kurtosis. Third, we assessed univariate normality visually using several univariate QQ-plots. Fourth, we assessed multivariate normality visually using a multivariate QQ-plot. Fifth, we assessed the linearity assumption visually using scatterplots that included both a linear regression line and a non-parametric loess regression line for each bivariate relation between variables.

In relation to traditional inferential statistics, we used the non-parametric alternatives to the one-way ANOVA, independent t-test, and paired t-tests (e.g., Kruskal-Wallis test, Wilcoxon rank-sum test, and Wilcoxon signed-rank test). This is because most of the study variables did not meet the normality assumption. Consistent with Appelbaum and colleague's (2018) suggestions, we included exact p-values as we employed null hypothesis significance testing (NHST) methods. In addition, we included effect size estimates to provide evidence of the practical importance of each inferential test conducted. We highlighted the significant main effects and interactions visually using state of the art violin plots, which simultaneously display the five-number summary of a set of data and the Kernel probability density of the observations at different values (Kassambara, 2021). Equally important, our sample size was much larger than almost all of the previous studies we have cited.

Regarding the complex data analysis of the two-step partially latent parallel mediation model of trait anxiety and cognitive control, we applied established item-parceling procedures (e.g., Houghton & Jinkerson, 2007) to create three continuous composite indicators for each latent variable. Analogous to employing non-parametric tests in traditional inferential statistics, we used maximum likelihood estimation with robust standard errors and Satorra and Bentler's (2001) adjusted fit indices considering the non-normality of the data. As recommended by Appelbaum and coauthors (2018), we included the associated correlation matrix, provided sufficient details of the models estimated, and identified the particular R library packages used to make it possible for interested readers to replicate our results.

Considering the above, by closely following the revised and updated JARS-Quant guidelines (Appelbaum et al., 2018), our study most probably meets high standards in reporting quantitative psychological research. However, some of the reviewed investigations on the relation between personality characteristics associated with emotional regulation and the purely cognitive aspects of task-switching and reversal learning employed less rigorous procedures to test their study hypotheses (e.g., Gul & Humphreys, 2014; Wilson et al., 2018). Next, we describe what are the general problems in the literature.

What are the most common problems in the literature?

There are some common problems in the literature that represent poor practices in conducting and reporting psychological research. Specifically, two highly problematic practices include selective analysis and selective reporting. These troublesome practices are subtle and require performing a critical reading of the scientific literature to be identified.

In relation to selective analysis, some researchers do not perform preliminary analyses to address missing values and evaluate the distributional assumptions of their data (e.g., Gul & Humphreys, 2014; Wilson et al., 2018). This poor practice is related to the incorrect understanding that traditional inferential tests are "apparently" robust even if the statistical assumptions are not met (Maronna et al., 2019). Therefore, it is common to use traditional parametric statistical tests when it would be more appropriate to employ a non-parametric or more robust alternative version of the statistical analyses. This is a malpractice that can have negative consequences on results because it involves forcing the data to fit statistical tests, as opposed to adapting the analytic strategy according to the particular characteristics of the data.

With respect to selective reporting, criticism of the excessive dependence on the p-value in the last decades has led to a systematic increase in the inclusion of estimates of effect sizes and confidence intervals in research reports (Nasser-Abu & Levy, 2009). For this reason, it is rare for a current study to rely solely on NHST methods. However, some recent investigations comply with this best practice approach consensus only in appearance (e.g., Gul & Humphreys, 2014; Hodgins & Adair, 2010; Janssen et al., 2018; Kessel et al., 2016; Liu et al., 2015; Nusbaum et al., 2018; Wilson et al., 2018). On the one hand, the requirement to report p-values alongside effect sizes and confidence intervals is usually met while presenting the results. On the other hand, there seems to be a subtle lack of transparency in the discussion with an overinterpretation of significant p-values and an underinterpretation of small effect sizes and large confidence intervals suggesting high uncertainty in the estimates. This half-hearted adherence to current reporting standards can perpetuate a cycle of confirmation bias or overly positive evaluations of the researcher's hypotheses.

In sum, seemingly unimportant acts or omissions while conducting and reporting psychological research can have great consequences in the quality of the investigation. For this motive, it is important to learn to read between the lines and be wary of poor research practices in the literature. Just as important, a moderate degree of self-criticism is necessary to recognize past mistakes and correct them with better practice approaches in the future. So, we provide a personal example of a poor research practice.

Personal example of a poor research practice

As recently as last May, I (graduate student: José A. Maldonado-Martínez) presented a poster that included poor research practices at the 2021 Association for Psychological Science (APS) Virtual Convention (Maldonado-Martínez et al., 2021). I used a Theil-Sen nonparametric regression to examine the influence of cognitive avoidance on the emotional counting Stroop (ECS) interference effect and found a direct and significant effect. So, the higher the cognitive avoidance levels, the greater the ECS interference effect. I concluded that these findings probably indicate that inhibiting the emotional processing of threatening stimuli requires extra processing capacity that slows performance on the primary task of identifying the number of words on the computer screen.

At a superficial level, I used best research practices while conducting and reporting our investigation. This is evidenced when an anonymous reviewer of the poster submission strongly agreed that 1) all critical results have been reported, 2) the results were clearly stated, 3) the analyses conducted were appropriate for addressing the research question, and 4) the conclusions drawn from the results are valid and appropriate. Equally important, the anonymous reviewer commented that the analysis plan and reporting of results in this application were impressive.

On the contrary, at a deeper level, I am aware that I used the poor research practices of selective analysis and selective reporting to fit our data to the statistical tests that would support our researcher's hypothesis (e.g., confirmation bias). For example, I chose to report the significant Spearman rank-order correlation and completely omit any mention of the nonsignificant Kendall's correlation. Moreover, I did not mention that the direct effect of cognitive avoidance on the ECS interference effect was nonsignificant when using a more robust version of the Theil-Sen nonparametric regression (e.g., with a higher standard error of the estimate). When interpreting the results, I highlighted the significant direct effect and downplayed the possible low practical importance of the finding (e.g., small effect size and large confidence intervals that suggest uncertainty in the estimate). My lack of transparency in reporting the results had no negative consequences, instead I was given the personal incentive of adding a poster presentation as first author at a prestigious international conference to my curriculum vitae (CV). I personally acknowledge these acts publicly with the commitment to uphold my ethical integrity in future projects.

It is well known that there is a strong pressure to publish in psychological science since frequent publication is associated with more fundings for the research institutions and better academic positions for the individual scholars. As happened to me, other researchers have probably resorted to unethical practices in order to increase their number of publications and give a boost to their CV. These poor research practices tend to be subtle and hide behind a lack of transparency in conducting and reporting psychological investigations. A practical example might be to use the space limit of the academic journal as an excuse to avoid discussing issues that could undermine the validity of the researcher's hypotheses (e.g., whether the data met the distributional assumptions that support using the inferential test employed).

Whether intentionally or not, the bottom line is that there is research in the psychological literature that manage to get published despite not meeting recommended quality standards. In the next subsection we perform a critical analysis of poor research practices in published empirical articles that are relevant to paths 5 to 12.

Critical analysis of poor research practices in published empirical articles that are relevant to paths 5 to 12

We found conflicting evidence between our results and the work of others (e.g., Gul & Humphreys, 2014; Hodgins & Adair, 2010; Janssen et al., 2018; Kessel et al., 2016; Liu et al., 2015; Nusbaum et al., 2018; Wilson et al., 2018) regarding the relation between personality characteristics associated with emotional regulation and the purely cognitive aspects of task-switching cost and reversal learning. For this motive, we conducted a critical analysis of poor research practices in published empirical articles that are relevant to paths 5 to 12. We focused on evaluating an empirical article for each path when it was available (e.g., there are currently no previous studies on the relation between decentering and reversal learning [path 10]). Specifically, our critical analysis consists of 1) describing the statistical tests employed, 2) criticizing the inadequate application of the statistical tests employed, and 3) suggesting alternative statistical tests that could have been employed to improve the quality of the findings.

Critical analysis of poor research practices in a published empirical article relevant to path 5. Direct effect of trait anxiety on task-switching cost

In psychology, the law of parsimony is "the principle that the simplest explanation of an event or observation is the preferred explanation" (VandenBos, 2015, p. 591). Although researchers should strive to be parsimonious, this should not be confused with implementing overly simplistic procedures that ignore complicated factors or details. In quantitative research, the fine line between using a parsimonious statistical model and a simplistic one can be so thin that crossing it can go unnoticed even in peer-reviewed journals. This is the case of the study by Gul and Humphreys (2014), who used a simple linear regression to examine the direct effect of anxiety on task-switching cost. These authors found a significant direct effect and concluded that the higher the anxiety the larger the switch cost (Gul & Humphreys, 2014).

At a superficial level, Gul and Humphreys (2014) employed the appropriate statistical test to examine the predictive role of a continuous predictor variable on a continuous criterion variable. However, we consider that their data analytic strategy was too simplistic. Beyond excluding outliers, Gul and Humphreys (2014) omitted any mention of whether the data met the linear regression assumptions (Field, 2017): 1) linearity of the data, 2) normality of residuals, homogeneity of residuals variance, and 4) independence of residuals error terms. Failure to meet any of the above assumptions would make the use of a simple linear regression inappropriate. Unfortunately, it is commonly understood that the distributional assumptions were met unless the authors explicitly state otherwise. This presumption of normality is quite ironic since the opposite scenario is much more common in practice.

We believe that Gul and Humphreys (2014) could have improved the quality of their findings if they had used any of the following three alternative models. First, we would recommend using a simple regression with bootstrap-corrected confidence intervals and significance values, which do not rely on the assumptions of normal distribution or homogeneity of variances. Second, we would suggest using a Theil-Sen non-parametric regression, which is a distribution-free alternative to the simple linear regression and thus is a robust estimator when analyzing data with distributional problems. Third, we would propose using a Siegel repeated median non-parametric regression, which is even more robust than the Theil-Sen non-parametric regression. Future studies that reproduce the procedures of Gul and Humphreys (2014) but replacing simple linear regression with any of these best practice statistical models should be encouraged.

Critical analysis of poor research practices in a published empirical article relevant to path 6. Direct effect of trait anxiety on reversal learning

An important reason for limiting the role of significance testing in the revised and updated JARS-Quant standards (Appelbaum et al., 2018) is that observed statistical significance, or p-values can change when using more robust versions of traditional statistical tests. Differences in estimated p-values across distinct alternative tests are not usually great, but slight variations in the p-value can make big differences in hypothesis testing, such as p=.051 (e.g., nonsignificant effect) versus p=.049 (e.g., significant effect) for the same effect when testing at the alpha=.05 level. A practical example of this issue is illustrated in the investigation by Wilson and colleagues (2018), who used the traditional independent samples t-test to examine whether there was a significant main effect of anxiety level on reversal learning ability. These researchers (Wilson et al., 2018) found a significant between-group difference in reversal learning, but the estimated p-value was .049.

Although this is a valid interpretation of the results from the NHST framework, it is ethically inappropriate for these investigators (Wilson et al., 2018) to downplay the small magnitude of the effect size (Cohen's d=0.32). Just as important, Wilson and coauthors (2018) did not mention whether their data met the assumptions of the traditional independent samples t-test (Field, 2017): 1) independence of observations, 2) no significant outliers, 3) normality, and 4) homogeneity of variances. Failure to meet any of these assumptions would render the use of the traditional independent samples t-test inappropriate. Exposing distributional problems in the data would make it necessary to use the more conservative alternatives to the independent samples t-test, which could raise the p-value above the widely accepted .05 threshold and change a significant finding to a non-significant one.

Data from studies that combine self-report instruments and performance measures in a cognitive computerized paradigm are highly unlikely to be exempt from distributional problems. For this reason, we would have recommended Wilson and collaborators (2018) to use the following three alternative analyses in gradual order according to the messiness of the data. First, when the only problem is the heterogeneity of variances, Welch's t-test should be used, which do not assume that the variance is the same in the two groups. Second, when there are significant outliers and heterogeneity of variances, Yuen's test for trimmed means should be used, which do not assume homogeneity of variances and excludes the top and bottom 20 percent of the observations (e.g., where the potential outliers could be located). Third, when there are significant outliers, heterogeneity of variance, and non-normality, Wilcoxon rank-sum test should be used, which is the non-parametric alternative to the traditional independent samples t-test. We understand that applying the statistical analyses that are best suited to the particular characteristics of the data could make a difference in producing reliable findings, whether significant or not, that could be successfully replicated in future research.

Critical analysis of poor research practices in a published empirical article relevant to path 7. Direct effect of cognitive flexibility on task-switching cost

Psychological science is constantly evolving, and the best practice methods of the past may become anachronistic in the near future. An example of this is the study conducted by Liu and collaborators (2015). These authors (Liu et al., 2015) were interested in examining whether cognitive flexibility could modulate task-switching cost. For this reason, they (Liu et al., 2015) conducted a three-way ANOVA with switch cost as the dependent variable, group (high vs low cognitive flexibility) as the between-subject factor, and congruency (congruent vs incongruent), and task-sequence (repeat vs switch) as the two within-subject factors. A significant three-way interaction was found, demonstrating that while switch costs for congruent and incongruent conditions were symmetrical in the high cognitive flexibility group, participants with low cognitive flexibility showed larger switch costs for congruent than incongruent trials.

Liu and collaborators (2015) used a balanced design (e.g., equal sized groups), which mainstream psychology has considered since the 1960s as a sufficient condition for the three-way mixed ANOVA to be robust to violations of assumptions (Wilcox, 2017). Hence, beyond excluding outliers, these authors (Liu et al., 2015) omitted any mention of meeting the three-way mixed ANOVA assumptions: 1) normality, 2) homogeneity of variances, and 3) sphericity. Contrary to conventional beliefs, recent investigations have shown serious practical problems (e.g., low statistical power) that expose the false sense of security in the use of traditional techniques to analyze data that do not meet distributional assumptions (Wilcox, 2017).

Although there is no non-parametric test that is equivalent to the three-way mixed ANOVA, Wilcox (2017) developed various methods of robust estimation and hypothesis testing for comparing groups in three-way designs. Specifically, we would have recommended Liu and coauthors (2015) to use the *WRS* package (Wilcox & Schönbrodt, 2021) and the *bwwtrim* function to perform a robust global test based on 20% trimmed means in a three-way design with 1 between- and 2 within-subjects factors. The significant three-way interaction could be inspected using the *WRS* package (Wilcox & Schönbrodt, 2021) and the *con3way* function for examining the multiple comparisons. We consider that it is important that researchers are willing to continue learning about the new collection of improved statistical analyses that provide an ever-increasing comprehension of the data.

Critical analysis of poor research practices in a published empirical article relevant to path 8. Direct effect of cognitive flexibility on reversal learning

As far as we know, no previous study has examined the effect of a self-report measure of cognitive flexibility on a behavioral measure of reversal learning. Instead, when comparing our results with the work of others, there was a tendency on the revised studies towards using reversal learning as a standard indicator of cognitive flexibility (Nusbaum et al., 2018). For instance, Nusbaum and colleagues (2018) conducted two separate one-way ANOVAs to evaluate between-group differences (negative, neutral, and positive mood) regarding learning in the initial acquisition phase and adaptation after the change of contingencies in the reversal learning paradigm. These researchers (Nusbaum et al., 2018) found no significant effects of mood on learning in the initial acquisition phase, nor on adaptation after the change of contingencies (e.g., reversal learning score as an indicator of cognitive flexibility ability).

Even though it is respectable that Nusbaum and coauthors (2018) were transparent in reporting their nonsignificant results, we understand that their data analytic strategy was too simplistic. These authors were lenient in their description of missing values as they merely mentioned that "… some participants skipped questions and thus are not included in these analyses" (Nusbaum et al., 2018, p. 5). Moreover, they (Nusbaum et al., 2018) did not report any problems with data distributions that could affect the validity of the findings. Specifically, to conduct a one-way ANOVA it is necessary that the data meet the following assumptions (Field, 2017): 1) independence of observations, 2) no significant outliers, 3) normality, and 4) homogeneity of variances. This is not a trivial matter since problems controlling for the probability of a Type I error (e.g., the probability over random samples that a true null hypothesis will be rejected) can arise even under normality with equal sized groups but heterogeneity of variances (Wilcox, 2017).

We understand that Nusbaum and coworkers (2018) could have employed the following statistical analyses depending on the magnitude of the distributional problems in the data. First, when the only problem is the heterogeneity of variances, Welch's ANOVA should be used, which do not assume that the variance is the same across groups. Second, when there are significant outliers and heterogeneity of variances, robust Welch's ANOVA with 20% trimmed means should be used, which do not assume homogeneity of variances and excludes the top and bottom 20 percent of the observations. Third, when there are significant outliers, heterogeneity of variances, and non-normality, Kruskal-Wallis test should be used, which is the non-parametric alternative to the traditional one-way ANOVA. Equally important, it would be necessary to apply a Bonferroni correction to reduce the probability of making a Type I error when testing multiple hypotheses. Alternatively, if the distributional assumptions were met, it would be preferable to perform a one-way MANOVA (e.g., there were two dependent variables) as opposed to conducting two separate ANOVAs.

Critical analysis of poor research practices in a published empirical article relevant to path 9. Direct effect of decentering on task-switching cost

There is a clear tendency in the psychological literature for favoring the use of traditional statistical techniques without performing preliminary data analytic procedures. As a case in point is the research by Kessel and collaborators (2016). These investigators (Kessel et al., 2016) were focused in examining the relation between two measures of decentering (e.g., accepting self-perception and distanced perspective) and two measures of the ability to shift attention (e.g., mean reaction time of the incongruent task and mean interference). Consequently, they (Kessel et al., 2016) used Pearson's correlations for testing their research hypotheses and found that none of the correlations were significant.

An uncritical reading of Kessel and coauthor's (2016) study would suggest that it was appropriate to use Pearson's correlations to examine the bivariate association between each pair of continuous variables. The decision to use the traditional Pearson's correlations would be justified if the linearity and normality assumptions were met (Field, 2017). Nonetheless, the authors (Kessel et al., 2016) omitted any mention of assessing the distributional assumptions. This is a poor research practice since employing standard tests when there are unidentified distributional problems could negatively affect the validity of the findings. It leaves much to be desired that many peer-reviewed journals (e.g., BMC Psychology [Kessel et al., 2016], Collabra: Psychology [Nusbaum et al., 2018], Global Journal of Human Social Science [Gul & Humphreys, 2014], PLoS ONE [Wilson et al., 2018]) continue to accept manuscripts for publication without requiring more rigorous preliminary analyses of the data.

It is highly unlikely that a variable that is calculated from the difference of two scores (e.g., mean interference) has a normal distribution. For this reason, we consider that Kessel and coauthors (2016) could have improved the quality of their findings by employing any of the following alternative statistical techniques that consider the possible lack of normality in some of the variables. On the one hand, a plausible solution could be using the Pearson's correlations with bootstrapped 95% confidence intervals, which are unaffected by the distribution of scores. On the other hand, a best practice approach could be using either the nonparametric Spearman's or Kendall's rank correlation coefficients. Especially, we would recommend Kessel and colleagues (2016) to use the Kendall's correlation since its estimates tend to be reliable in small samples as in their study (*N*=55).

Critical analysis of poor research practices in a published empirical article relevant to path 10. Direct effect of decentering on reversal learning

As previously discussed, there is a gap in the literature regarding the association between decentering and reversal learning. This is because decentering tends to be considered as a personality characteristic through which mindfulness exerts its positive effects on emotional regulation (Hayes-Skelton & Graham, 2013). However, much less is known in relation to the effect of decentering on purely cognitive aspects. To the best of our knowledge, Kessel and coauthors (2016) conducted the only investigation that has explicitly evaluated the correlation between decentering and executive attention (e.g., ability to shift attention). Therefore, beyond the study by Kessel and coworkers (2016) that we critically reviewed in the previous subsection, there are currently no published empirical articles that are relevant to the direct effect of decentering on reversal learning.

Critical analysis of poor research practices in a published empirical article relevant to path 11. Direct effect of dispositional mindfulness on task-switching cost

When researchers use traditional statistical methods to analyze multilevel data, the assumption of independent errors is generally not met, which could result in an inappropriate estimate of the standard error and an increased Type I error rate (Finch et al., 2014). This is the case of Hodgins and Adair (2010), who recruited their participants (*N*=96, 67% females, ages 21-79) from two meditation centers and one monastery in northeastern USA. However, they (Hodgins & Adair, 2010) ignored the hierarchical structure (e.g., Level 2: data collection site, Level 1: individuals) of their data and applied a standard ANCOVA to examine between-group differences in the number of correct identifications in the perspective switching task among groups (meditators/non-meditators) and sex (male/female), while controlling for age. These researchers (Hodgins & Adair, 2010) found that meditators identified more alternative perspectives in ambiguous still images than non-meditators, while the effect of sex was nonsignificant.

Hodgins and Adair (2010) made several logical mistakes in their data analytic strategy. On the one hand, it was not assessed whether individuals clustered within a higher-level unit (e.g., data collection site) were more similar among themselves compared to participants from other clusters, and thus determine whether or not a multilevel model is even necessary. On the other hand, all information concerning assumptions and issues in ANCOVA was not reported. This is a poor research practice since ANCOVA makes the following assumptions about the data (Field, 2017): 1) independence of the covariate and treatment effect, 2) linearity between the covariate and the outcome variable, 3) homogeneity of regression slopes, 4) the outcome variable should be approximately normally distributed, 5) homogeneity of residuals variance for all groups, and 6) no significant outliers. Failure to meet any of these assumptions would make the use of a standard ANCOVA inappropriate and would require using robust versions of this test.

We would have recommended to Hodgins and Adair (2010) to calculate the intraclass correlation (ICC), which estimates "the correlation among individual's scores within the cluster or nested structure" (Finch et al., 2014, p. 24). An ICC close to 0 would rule out the need to use a multilevel model, while the opposite would be true as the ICC approaches 1. Even in the scenario where the ICC justifies ignoring the hierarchical structure of the data, it is still highly unlikely that all the assumptions of the standard ANCOVA will be met. For this reason, we would suggest using the *WRS2* package (Mair & Wilcox, 2020) and the *ancova* function which compares 20% trimmed means at different points along the covariate without requiring that distributional assumptions are met. Even more robust, it would be to use the *ancboot* function from the *WRS2* package (Mair & Wilcox, 2020), which does the same as *ancova* but computes confidence intervals using a percentile t-bootstrap. Both modern methods represent best practice approaches with increased accuracy and power compared to the conventional approach to perform ANCOVA (Wilcox, 2017).

Critical analysis of poor research practices in a published empirical article relevant to path 12. Direct effect of dispositional mindfulness on reversal learning

A common type of confirmation bias consists in finding a single significant model and giving an overly positive evaluation of the results, while minimizing the importance of evidence that contradicts the researcher's hypotheses (Kline, 2016). This problem is generally found in studies where the primary hypotheses were not supported, and researchers perform several post hoc exploratory analyses to identify statistically significant associations that were not established a priori in the research design. An example of this is the investigation by Janssen and colleagues (2018) where they conducted a 2 X 2 mixed ANOVA to examine the effect of time (pre and post) and intervention (mindful eating or educational cooking) on reversal learning. None of the main effects or interactions were statistically significant. However, the authors (Janssen et al., 2018) observed large individual differences in time invested in the intervention programs and performed post hoc zero-order Pearson's correlations between time invested and change in reversal learning separately for both groups. The association was significant for the mindful eating condition and nonsignificant for the educational cooking group.

Based on the findings of their exploratory post hoc zero-order correlations, Janssen and coworkers (2018) concluded that time invested in mindful eating, but not the educational cooking condition was associated with positive changes in reversal learning. Nevertheless, results of zero-order correlations, where nothing has been controlled for, are a weak source of evidence for a study in which the main hypotheses were not supported. In other words, these investigators (Janssen et al., 2018) used the subtle poor practices of selective analysis and selective reporting to overemphasize the appropriateness of their hypotheses (e.g., confirmation bias). However, no effort was made to incorporate the time invested in the intervention programs continuous variable into more complex models that could rule out the possibility that the significant zero-order correlation found was spurious and would become nonsignificant when controlling for other variables.

We understand that Janssen and coworkers (2018) could have improved the quality of their findings by using a statistical model that consider the effect of the time invested in the intervention programs as a covariate. For example, we would have recommended using a 2 X 2 mixed model ANCOVA to examine the effect of time (pre and post) and intervention (mindful eating or educational cooking), while controlling for the effect of time invested in the intervention programs (e.g., covariate) on reversal learning. A hypothetical significant main effect of the intervention would indicate that after considering the variability in the covariate, the mindful eating group showed higher reversal learning scores than their counterparts in the educational cooking condition. This would be a much more reliable follow-up post hoc analysis than simply computing zero-order correlations that were completely unrelated to the original hypotheses.

Alternatively, a best practice approach could be using a longitudinal multilevel model that consider the repeated measurements (Level 1) as nested within the individuals (Level 2). Modeling longitudinal data in a multilevel framework has several advantages over more traditional methods of longitudinal analysis (e.g., Mixed model ANCOVA). For example, a multilevel approach allows to simultaneously evaluate how an individual changes over time (Level 1) and the differences in temporal change across individuals (Level 2). We would have suggested using a longitudinal multilevel model analogous to the 2 X 2 mixed model ANCOVA but considering that there will be a separate intercept (e.g., the mean of the dependent variable when the value of the predictor variables is 0) for each individual. There is a trend in recent investigations to favor the use of multilevel models over traditional approaches to adapt the data analytical strategy to the context in which the studied phenomena occur (Hair & Fávero, 2019; Murrar & Brauer, 2018).

Summary of the critical analysis of poor research practices in published empirical articles

We strove to follow a coherent approach in our critical analysis of poor research practices in published empirical articles examining the association between personality characteristics related to emotional regulation and behavioral measures of cognitive control. For this motive, we began the discussion by pointing out the importance of journal article reporting standards in producing high-quality and reproducible psychological research. For example, reporting standards help by providing more complete descriptions of the conditions necessary to replicate the results (Aarts et al., 2015). In other words, a comprehensive "reporting of the critical aspects of design and results enables researchers to figure out what caused the difference in outcomes when new studies do not replicate the results of older ones" (Cooper, 2020, p. 189).

Next, we explained how we meet high standards in reporting quantitative psychological research in the current investigation. Specifically, we followed Cooper's (2020) advice to use the revised and updated JARS-Quant standards (Appelbaum et al., 2018) as a checklist while performing the statistical analyses and reporting the results. We provided a through description on how we 1) inspected and addressed the missing data, 2) evaluated the distributional assumption of multivariate normality, 3) replaced traditional inferential analyses with its non-parametric alternatives, and 4) performed the two-step partially latent parallel mediation model of trait anxiety and cognitive control. For the above reasons, we consider that it is highly likely that our study meets high standards in reporting quantitative psychological research.

Then, we exposed what are the most common problems in the literature. Precisely, two troublesome poor practices that prevail in the psychological literature are selective analysis and selective reporting. These issues are subtle and require the ability of reading between the lines to be identified. On the one hand, selective analysis is evident in studies that do not assess the distributional assumptions and therefore incorrectly use traditional parametric statistical tests when it would be more appropriate to employ an alternative non-parametric or robust method. On the other hand, selective reporting consists of overemphasizing evidence that favors the researcher's hypothesis (e.g., p-value < .05) and downplaying evidence that contradicts the practical importance of the findings (e.g., low effect size or large confidence intervals). Both of these poor practices contribute to perpetuating a cycle of confirmation bias, as the psychological science still places too much weight on the NHST framework in accepting manuscripts for publication.

Afterwards, I (graduate student: José A. Maldonado-Martínez) described a personal experience where I used the poor research practices of selective analysis and selective reporting for submitting a poster presentation at the 2021 Association for Psychological Science (APS) Virtual Convention (Maldonado-Martínez et al., 2021). There were no negative consequences for intentionally ignoring evidence that would contradict the study's hypothesis, as the poster proposal was successfully accepted at the convention. In the same way, it is likely that other researchers have resorted to unethical practices due to the strong pressure to publish in psychological science. Even if these poor practices are used inadvertently, the problem persists that there is research that manages to be published despite not meeting recommended APA Style (Appelbaum et al., 2018) quality standards.

Finally, we performed a critical analysis of poor research practices in published empirical articles relevant to paths 5 to 12. The malpractices of selective analysis and selective reporting were prevalent through the reviewed investigations, albeit with varying degrees of subtlety. At one end, Wilson and colleagues (2018) overinterpreted their almost nonsignificant result (p=.049) in favor of their researcher's hypothesis, which is an obvious form of confirmation bias. At the other extreme, Janssen and coworkers (2018) found a significant result in a post hoc analysis and with subtle eloquence they managed to minimize the importance of contradictory evidence, while giving an overly positive evaluation of the results.

Preliminary analyses to assess the distribution of the data were rarely conducted in the reviewed empirical articles because researchers (Gul & Humphreys, 2014; Hodgins & Adair, 2010; Janssen et al., 2018; Kessel et al., 2016; Liu et al., 2015; Nusbaum et al., 2018; Wilson et al., 2018) seem to wrongly believe that traditional statistical tests produce reliable estimates even when not meeting the parametric tests assumptions. Hence, when selective analysis is used, the data are forced to fit the statistical test with a higher probability of producing a significant result, rather than using the data analytic method that best fits the particular characteristics of the data.

Then, when selective reporting is used, the results obtained by incorrect techniques are overinterpreted in favor of the researcher's hypotheses.

The root of the problem appears to be that the majority of psychological researchers have been trained in the NHST framework and are therefore overly dependent on obtaining a significant result (e.g., $p<.05$). At the same time, most researchers seem to ignore that p-values represent the "likelihood of a sample result or one even more extreme assuming random sampling under a true null hypothesis (e.g., every result happens by chance in the population) and where all other assumptions are met" (Kline, 2016, p. 55). In other words, p-values are calculated assuming that the null hypothesis is already true, so it should be assumed that sampling error is the only explanation for a significant result (Kline, 2016). For this motive, the JARS-Quant (Appelbaum et al., 2018) recommends reporting significant results with their associated effect sizes and confidence intervals to address the practical importance and uncertainty of the findings, respectively.

Although there is a tendency to include measures of effect sizes and confidence intervals when reporting results, it is still common to prioritize statistical significance when discussing findings (e.g., Gul & Humphreys, 2014; Hodgins & Adair, 2010; Janssen et al., 2018; Kessel et al., 2016; Liu et al., 2015; Nusbaum et al., 2018; Wilson et al., 2018). Assigning too much weight to statistical significance when discussing the results contributes to maintaining a cycle of misinformation that does not promotes progress in psychological science. This is because overly positive interpretations of results based on significance testing represent an unreliable source of evidence that could mislead other researchers into formulating study hypotheses that are unlikely to be supported. In contrast, establishing a comprehensive discussion of effect sizes and confidence intervals contextualized within the particular research area would constitute a best practice approach to producing high-quality and reproducible research.

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Appendix A: Cognitive Flexibility Inventory (CFI)

Código: __________

CFI

Por favor usa la escala abajo para indicar cuan de acuerdo o en desacuerdo estás con las siguientes aseveraciones.

Muy en desacuerdo	Desacuerdo	Algo en desacuerdo	Neutral	Algo en acuerdo	De acuerdo	Muy de acuerdo
1	2	3	4	5	6	7

1. Soy bueno en sacar de proporción las situaciones.	1	2	3	4	5	6	7
2. Se me dificulta tomar decisiones cuando me enfrento a situaciones difíciles.	1	2	3	4	5	6	7
3. Considero múltiples opciones antes de tomar una decisión.	1	2	3	4	5	6	7
4. Cuando me encuentro con situaciones difíciles, siento que pierdo el control.	1	2	3	4	5	6	7
5. Me gusta ver las situaciones difíciles desde diferentes ángulos.	1	2	3	4	5	6	7
6. Busco información adicional, no disponible en el momento, antes de atribuir causas a una conducta.	1	2	3	4	5	6	7
7. Cuando me enfrento con situaciones difíciles, me estreso y no puedo pensar en una manera de resolver la situación.	1	2	3	4	5	6	7
8. Trato de pensar las cosas desde el punto de vista de otra persona.	1	2	3	4	5	6	7
9. Me parece fastidioso que hayan tantas maneras de hacer frente a situaciones difíciles.	1	2	3	4	5	6	7
10. Soy bueno poniéndome en los zapatos ajenos.	1	2	3	4	5	6	7
11. Cuando me encuentro con situaciones difíciles, no sé qué hacer.	1	2	3	4	5	6	7
12. Es importante tomar en cuenta las situaciones difíciles desde distintos ángulos.	1	2	3	4	5	6	7
13. Cuando me encuentro con situaciones difíciles, considero múltiples opciones antes de decidir cómo comportarme.	1	2	3	4	5	6	7
14. A menudo miro una situación desde distintos puntos de vista.	1	2	3	4	5	6	7
15. Soy capaz de superar las dificultades a las que me enfrento en la vida.	1	2	3	4	5	6	7
16. Considero todos los hechos y la información disponible a la hora de atribuir causas a una conducta.	1	2	3	4	5	6	7
17. Siento que no tengo poder para cambiar las cosas en situaciones difíciles.	1	2	3	4	5	6	7
18. Cuando me encuentro con situaciones difíciles, me detengo y trato de pensar en varias maneras de resolverlas.	1	2	3	4	5	6	7
19. Puedo pensar en más de una forma de resolver una situación difícil.	1	2	3	4	5	6	7
20. Considero múltiples opciones antes de responder a situaciones difíciles.	1	2	3	4	5	6	7

Appendix B: Cognitive Avoidance Questionnaire (CAQ)

Código: ____________

CAQ

Las personas reaccionan de diferentes maneras a ciertos tipos de pensamientos. Usando la siguiente escala, por favor indica en qué medida las siguientes aseveraciones son típicas de la manera en que responderías a ciertos pensamientos. Por favor circula el número apropiado (del 1 al 5).

	Para nada típica	Un poco típica	Algo típica	Bastante típica	Totalmente típica
1. Hay cosas en las que preferiría no pensar.	1	2	3	4	5
2. Evito ciertas situaciones que me llevan a prestar atención a cosas en las que no quiero pensar.	1	2	3	4	5
3. Reemplazo imágenes mentales amenazantes con cosas que me digo a mí mismo.	1	2	3	4	5
4. Pienso en cosas que me preocupan como si le estuvieran pasando a alguien más.	1	2	3	4	5
5. Tengo pensamientos que intento evitar.	1	2	3	4	5
6. Trato de no pensar en los aspectos más incómodos de algunas situaciones para no asustarme tanto.	1	2	3	4	5
7. A veces evito objetos que me pueden provocar pensamientos incómodos.	1	2	3	4	5
8. Me distraigo para evitar pensar en ciertos asuntos perturbadores.	1	2	3	4	5
9. Evito personas que me hacen pensar cosas en las que no quiero pensar.	1	2	3	4	5
10. A menudo hago cosas para distraerme de mis pensamientos.	1	2	3	4	5
11. Pienso en detalles insignificantes para no pensar en asuntos importantes que me preocupan.	1	2	3	4	5
12. A veces me meto en una actividad para no pensar en ciertas cosas.	1	2	3	4	5
13. Para evitar pensar en asuntos que me incomodan, me obligo a pensar en otra cosa.	1	2	3	4	5

Continúa al dorso

	Para nada típico	Un poco típico	Algo típico	Bastante típico	Totalmente típico
14. Hay cosas en las que intento no pensar.	1	2	3	4	5
15. Repito cosas en mi cabeza para evitar visualizar situaciones que me asustan.	1	2	3	4	5
16. A veces evito lugares que me hacen pensar en cosas que preferiría no pensar.	1	2	3	4	5
17. Pienso en eventos pasados para no pensar en eventos futuros que me causan inseguridad.	1	2	3	4	5
18. Evito acciones que me recuerden cosas en las que no quiero pensar.	1	2	3	4	5
19. Cuando tengo imágenes mentales que son incómodas, me digo cosas en la cabeza para reemplazarlas.	1	2	3	4	5
20. Pienso en cosas irrelevantes para no pensar en asuntos más importantes.	1	2	3	4	5
21. A veces me mantengo ocupado(a) para evitar que me surjan pensamientos.	1	2	3	4	5
22. Evito situaciones que involucren personas que me hagan pensar en cosas desagradables.	1	2	3	4	5
23. En lugar de tener imágenes de eventos incómodos en mi mente, trato de describir los eventos usando un monólogo interno (cosas que digo en mi mente).	1	2	3	4	5
24. Me deshago de imágenes mentales relacionadas a una situación amenazante tratando de describir la situación usando un monólogo interno.	1	2	3	4	5
25. Pienso en cosas que le preocupan a otras personas en vez de pensar en mis preocupaciones.	1	2	3	4	5

¿Contestaste al dorso?

Appendix C: Mindful Attention Awareness Scale (MAAS)

MAAS
Experiencias del día a día

Código: __________

Instrucciones: En la parte de abajo se encuentra una colección de oraciones sobre tus experiencias diarias. Utilizando la escala del 1-6 abajo, por favor indica cuán frecuente o poco frecuente tienes cada experiencia. Por favor contesta según lo que refleja realmente tu experiencia en vez de pensar en cómo tu experiencia debería de ser. Por favor atiende cada oración como separada de las otras.

1	2	3	4	5	6
Casi Siempre	Muy Frecuente	Algo Frecuente	Algo Poco Frecuente	Muy Poco Frecuente	Casi Nunca

1. Podría estar sintiendo alguna emoción y no darme cuenta hasta algún tiempo después.	1	2	3	4	5	6
2. Rompo o derramo cosas por descuido, por no prestar atención o por estar pensando en otra cosa.	1	2	3	4	5	6
3. Encuentro difícil mantenerme enfocado en lo que está pasando en el momento presente.	1	2	3	4	5	6
4. Tiendo a caminar rápidamente a donde quiero ir sin prestar atención a lo que me pasa o siento mientras camino.	1	2	3	4	5	6
5. Tiendo a no darme cuenta de sensaciones de tensión física o de incomodidad hasta que éstas realmente me llaman la atención.	1	2	3	4	5	6
6. Se me olvida el nombre de una persona casi tan pronto me lo dicen por primera vez.	1	2	3	4	5	6
7. A veces parece que “estoy en automático”, sin estar muy consciente de lo que estoy haciendo.	1	2	3	4	5	6
8. Me apresuro haciendo cosas sin prestarles mucha atención.	1	2	3	4	5	6
9. Me enfoco tanto con la meta que quiero alcanzar que pierdo contacto con lo que estoy haciendo ahora mismo para poder alcanzarla.	1	2	3	4	5	6
10. Hago trabajos o tareas automáticamente, sin estar consciente de lo que estoy haciendo.	1	2	3	4	5	6
11. Me he encontrado escuchando a alguien con un oído, mientras hago otra cosa a la misma vez.	1	2	3	4	5	6
12. Guío a lugares en “piloto automático” y luego me pregunto por qué llegué ahí.	1	2	3	4	5	6
13. Me he encontrado preocupándome por el futuro o el pasado.	1	2	3	4	5	6
14. Me doy cuenta de que estoy haciendo cosas sin prestar atención.	1	2	3	4	5	6
15. Hago meriendas sin darme cuenta de que estoy comiendo.	1	2	3	4	5	6

Appendix D: State-Trait Anxiety Inventory - Trait (STAI-T)

Código _______

STAI-R

Abajo se presenta un número de aseveraciones que personas han usado para describirse a sí mismas. Lea cada aseveración y circule el número a la derecha para indicar como se siente *generalmente*. No hay contestaciones correctas o incorrectas. No emplee mucho tiempo en ninguna de las aseveraciones, pero provea la contestación que parezca describir cómo se siente por lo general.

	Nada	Algo	Bastante	Mucho
1. Me siento agradable.	0	1	2	3
2. Me siento nervioso/a e inquieto/a.	0	1	2	3
3. Me siento satisfecho/a conmigo mismo/a.	0	1	2	3
4. Desearía poder ser tan feliz como otros parecen estar.	0	1	2	3
5. Me siento como un fracaso.	0	1	2	3
6. Me siento descansado/a.	0	1	2	3
7. Soy una persona tranquila, serena y compuesta.	0	1	2	3
8. Veo que las dificultades se amontonan de manera que no puedo superarlas.	0	1	2	3
9. Me preocupo demasiado por algo que realmente no tiene importancia.	0	1	2	3
10. Soy feliz.	0	1	2	3
11. Tengo pensamientos inquietantes/perturbadores.	0	1	2	3
12. Me falta confianza en mí mismo/a.	0	1	2	3
13. Me siento seguro/a.	0	1	2	3
14. Tomo decisiones fácilmente.	0	1	2	3
15. Me siento insuficiente.	0	1	2	3
16. Estoy conforme.	0	1	2	3
17. Algunos pensamientos sin importancia rondan por mi mente y me incomodan.	0	1	2	3
18. Tomo las decepciones tan intensamente que no puedo sacarlas de mi mente.	0	1	2	3
19. Soy una persona estable.	0	1	2	3
20. Me pongo tenso/a y agitado/a cuando pienso sobre mis recientes preocupaciones e intereses.	0	1	2	3

Appendix E: Experiences Questionnaire (EQ)

EQ Código:________

Instrucciones: Clasifique cada una de las siguientes aseveraciones usando una escala del 1 ("Nunca") al 5 ("Todo el tiempo"). Por favor, no deje ninguna respuesta en blanco.

	Nunca				Todo el tiempo
1. Pienso sobre lo que va a suceder en el futuro.	1	2	3	4	5
2. Me recuerdo a mí mismo que los pensamientos no son hechos.	1	2	3	4	5
3. Soy capaz de aceptarme a mí mismo como soy.	1	2	3	4	5
4. Me percato de todo tipo de cosas pequeñas y detalles en el mundo que me rodea.	1	2	3	4	5
5. Soy más amable conmigo mismo cuando las cosas salen mal.	1	2	3	4	5
6. Puedo reducir la velocidad de mi pensar en momentos de estrés.	1	2	3	4	5
7. Me pregunto qué tipo de persona realmente soy.	1	2	3	4	5
8. No me dejo llevar tan fácilmente por mis pensamientos y sentimientos.	1	2	3	4	5
9. He notado que no tomo las dificultades tan personalmente.	1	2	3	4	5
10. Puedo separarme de mis pensamientos y sentimientos.	1	2	3	4	5
11. Analizo porqué las cosas terminan siendo como son.	1	2	3	4	5
12. Puedo tomarme tiempo en reaccionar a dificultades.	1	2	3	4	5
13. Pienso una y otra vez sobre lo que otros me han dicho.	1	2	3	4	5
14. Puedo tratarme amablemente.	1	2	3	4	5
15. Puedo darme cuenta de sentimientos incómodos sin verme obligado a manejarlos.	1	2	3	4	5
16. Tengo la sensación de que estoy totalmente consciente de lo que está ocurriendo a mi alrededor y en mi interior.	1	2	3	4	5
17. Puedo ver que en realidad no soy mis pensamientos.	1	2	3	4	5
18. Estoy consciente de la sensación de mi cuerpo como un todo.	1	2	3	4	5
19. Pienso sobre las maneras en las que soy diferente de otras personas.	1	2	3	4	5
20. Veo las cosas desde una perspectiva más amplia.	1	2	3	4	5