USING LATENT PROFILE ANALYSIS TO IDENTIFY RESPONSE STYLE SUBGROUPS ON THE PERSONALITY ASSESSMENT INVENTORY (PAI): IMPLICATIONS FOR PREDICTIVE VALIDITY

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DEDICATION

To my family – Thank you for your ever-present support and encouragement; it has meant the world to me and I couldn't have completed this journey without you.

To Porter, Henley George, and George – Thank you for all of the cuddles and companionship. Those late nights at my computer would have been far lonelier without you.

To my husband – Thank you for believing in me when my confidence waivered. Thank you for celebrating my wins and loving me through my losses, and for always helping me see the levity in life.

Finally, to my dual computer monitors – You are the real M.V.P.s

ABSTRACT

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Many self-report multiscale personality measures incorporate validity scales to allow clinicians and researchers to assess the trustworthiness of evaluee responses. However, the conventional scale-by-scale cut-score approach to validity scale interpretation is limiting because (1) there are multiple validity scales on the most popular measures, leading to the possibility of many different validity profiles across scales, and (2) it presumes a strong—but typically untested—moderating effect of response style on the association between substantive clinical scales and outcomes. In the current study, I performed a Latent Profile Analysis with the Personality Assessment Inventory (PAI; Morey, 1991) validity scale scores from 1,506 male Sexually Violent Predator (SVP) evaluees to sort offenders into response-style subgroups. The best fitting model was a four-class model: Honest Responders (*n* = 405, 26.89%), Positive Impression (*n* = 777, 51.59%), Negative Impression (*n* = 122, 8.10%) and Disengagement/Inattention (*n* = 202, 13.41%). I then examined whether response-style group membership moderated the association between select PAI scales (ANT, AGG, VPI, BOR, INT and EXT) and post-release recidivism. There were five statistically significant interaction effects across the 24 models, but the pattern of effects differed across models and there was no evidence of a consistent pattern of moderating effects. Overall, this study lends support to the utility of the PAI validity scales to delineate four theoretically consistent response styles. However, results from this study only minimally support the presumed strong moderating effect of response style which has primarily driven the conventional cut-score approach to validity scale interpretation.

KEYWORDS: Response style; Latent Profile Analysis; PAI; Sexually violent predator

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CHAPTER I

Introduction

Many self-report multiscale personality measures incorporate validity scales to allow clinicians and researchers to assess the trustworthiness of evaluee responses. Each scale is designed to assess a specific response style, with the four most common response styles being random responding, inconsistent responding, negative distortion, and positive distortion (Sellbom & Bagby, 2008). These types of scales are sometimes described using the broader term of validity scales because their overarching purpose is to identify protocols that cannot be interpreted (i.e., are invalid) due to concerns about response style. The validity of responses on self-report instruments is of particular importance in forensic cases, as evaluees often have external motivation to distort their responses (see Otto, 2002). In some cases, the motivation may be to appear severely ill or otherwise impaired (e.g., insanity, emotional injury), in others the motivation may be to appear symptom free (e.g., custody, risk assessment).

Researchers have estimated that the prevalence of malingering in criminal forensic cases ranges from 10% to 25% (Rogers et al., 1998; Rogers et al., 1994; Cornell & Hawk, 1989; Lewis et al., 2002; Heinze, 2003). Although forensic evaluators can use measures specifically designed to detect feigning when they suspect malingering (e.g., SIRS-2; Rogers et al., 2010), many also use multiscale inventories in these cases, especially inventories with imbedded validity scales (see Borum & Grisso, 1995; McLaughlin & Kan, 2014). For example, one study of more than 100 forensic evaluators found that 57% reported using multiscale inventories frequently or almost always when assessing response style (McLaughlin & Kan, 2014).

The conventional approach for using validity scale scores is to use manual recommended cut scores to classify the entire profile as either valid or invalid. If the profile is deemed invalid, the clinician does not interpret scores on any clinical or content scales from the measure. If the profile is deemed valid, the clinician provides an interpretation, sometimes urging caution if the validity scale scores are elevated but not in the invalid range. This approach has been criticized by scholars who have argued that the real-world utility of validity scale cut scores is not supported by research, indicating weaker construct validity for clinical scale scores when validity scale scores are in the invalid range (Piedmont et al., 2000). There is also a considerable possibility that validity scale scores used to classify profiles as invalid are capturing—to some extent—meaningful aspects of personality and psychopathology (Diener et al., 1991; Morey et al., 2002). Use of the cut-score approach is also complicated by the presence of multiple validity scale scores on most measures, leading to the possibility of many different validity scale profiles for the same measure.

Although many studies show that research participants believed to be feigning score higher on self-report measure validity-scale scores than those presumed to be responding honestly (e.g., Rogers et al., 2003; Hawes & Boccaccini, 2009; Sharf et al., 2017), most researchers report separate analyses for each individual validity scale score and do not consider patterns of scores across multiple scales. Moreover, few studies have examined whether clinical and content scale scores from evaluees with elevated validity scale scores actually possess weaker concurrent or predictive validity than those from evaluees with lower scorers. In other words, few studies have examined whether validity scale scores moderate the association between the clinical scales, which are the main focus of multiscale inventories, and important concurrent or future outcomes (e.g., diagnosis, prognosis, risk). The cut-score approach appears to presume a strong moderating effect, assuming clear associations between clinical scale scores and outcomes when the profile is valid and no association when the profile is invalid. Results from studies that have examined this moderation question have produced mixed results, with some studies finding a moderating effect for validity scale scores (e.g., Edens & Ruiz, 2005, 2006; Gardner & Boccaccini, 2017) and others finding no moderating effect (Piedmont, et al., 2000; McGrath et al., 2010).

In the current study, I considered whether classifying evaluees into empirically defined response-style subgroups based on their scores across validity scales provided more useful information for clinical practice than following the scale-by-scale cut-score approach described in manuals and used by practitioners. Specifically, I used Latent Profile Analysis (LPA) with validity scale scores from a widely used multiscale inventory [Personality Assessment Inventory (PAI), Morey, 1991, 2007] to classify risk assessment evaluees into empirically derived response-style subgroups, and then examined whether associations between clinical scale scores and measures of concurrent and predictive validity differed for the response style subgroups. This subgroup approach could result in fewer profiles being deemed invalid, and a more nuanced picture of profile validity.

PAI Validity Scales and Indices

Many multiscale inventories include imbedded validity scales to assist in the interpretation of evaluee response profiles. The four main response styles that are the focus of multiscale inventories include random responding, inconsistent responding, negative distortion (overreporting of symptomology) and positive distortion (underreporting of symptomology) (Sellbom & Bagby, 2008). The PAI, which is the focus of this study, includes validity, index, and discriminant function designed to assess each of these four response styles.

The PAI is a multiscale, self-report, 344-item broadband inventory that provides scores on 11 clinical scales, five treatment scales, two interpersonal scales, and four validity scales. Although Morey (1991) designed the PAI to include four validity scales, there are now as many as eleven PAI scales designed to aid in response-style interpretation. The four PAI validity scales are Inconsistency (INC), Infrequency (INF), Negative Impression Management (NIM), and Positive Impression Management (PIM). Validity scales consist of items specifically generated for assessing response style on the PAI. PAI supplemental scores are based on a combination of validity and clinical scales. These include index scores [Malingering Index (MAL), Defensiveness Index (DEF)], which are based on patterns of scale and subscale cut scores, and discriminant function scores [Roger's Discriminant Function (RDF), Cashel's Discriminant Function (CDF)], which are based on weighted combinations of scale and subscale scores. Additionally, Morey and Hopwood (2004) developed a protocol for assessing random responding on the back portion of the assessment only.

Researchers have also developed two additional measures for detecting over-reporting on the PAI: the Negative Distortion Scale (NDS; Mogge et al., 2010) and the Multiscale Feigning Index (MFI; Gaines et al, 2013). These scales are based on combinations of scale (MFI) or item (NDS) scores that researchers have found to be empirically related to feigning. Although these scores are not included as part of standard scoring procedures, they are straightforward to calculate when scale (MFI) or item scores (NDS) are available.

Random and Inconsistent Responding

Assessing random and inconsistent responding on a multiscale measure is imperative, as it speaks to the level of care and attention the evaluee is taking when answering the questionnaire. There can be multiple reasons that an individual appears to be responding randomly or inconsistently including carelessness, confusion, illiteracy, or even language barriers. The PAI has one validity scale to detect inconsistent responding and one to assess random responding. The Inconsistency (INC) scale was designed to assess how similarly an evaluee responds to 10 pairs of items of similar content. The PAI manual (Morey, 1991, 2007) indicates that T-scores under 64 are valid, T-scores between 64 and 72 are moderately elevated and should be viewed with caution, and T-scores over 73 are elevated and invalid. Research has indicated that INC is effective at identifying random responding at various cut points (*AUC* = .91; Edens & Ruiz, 2005).

Morey developed the Infrequency (INF) scale to assess random responding through atypical item endorsement. The items of the INF scale were selected for their low endorsement rate across normal and clinical participants. The PAI manual indicates that T-scores under 60 are valid, T-scores between 60 and 74 are moderately elevated and should be viewed with caution, and T-scores over 75 are elevated and invalid. Research has indicated that INF performs well when detecting random responding (*AUC* = .95; Clark et al., 2003). However, research has also indicated that INF might be slightly elevated in correctional settings when compared to community settings, due to particular experiences while incarcerated (*d* = .62; Edens & Ruiz, 2005). Regarding back-random responding, Morey and Hopwood (2004) encourage calculating the difference between the PAI short form T-score and the full form T-score on the Suicidal Ideation (SUI) and Alcohol Problems (ALC) scales. If the absolute value of both differences is greater than five, back random responding should be suspected. Research has demonstrated the efficacy of this procedure in community (specificity = .97; Morey & Hopwood, 2004) and clinical (specificity = .91; Morey & Hopwood, 2004) samples. In a psychiatric sample, the sensitivity of this procedure decreased as the number of randomly responded items decreased from 200 (sensitivity = .77) to 50 (sensitivity = .32; Siefert et al., 2007).

Negative Distortion

Scores on measures designed to detect negative distortion provide information about the extent to which an evaluee is attempting to present themselves in a negative light. The PAI has one validity scale specifically designed to assess negative distortion. The Negative Impression Management (NIM) scale consists of items that indicate rare and often improbable symptoms, with low endorsement in both normal and clinical samples. The PAI manual indicates that T-scores under 73 are valid, T-scores between 73 and 83 are moderately elevated and should be viewed with caution, and T-scores over 92 are elevated and invalid.

Although Morey (1991, 2007) designed NIM to provide information about impression management, it is not a feigning scale. NIM items are more likely to be endorsed in clinical populations than normal populations; consequentially, clinical evaluees with severe symptomology are likely to endorse these items and may have elevated NIM scores naturally. Meta-analytic findings across studies support the potential utility of this scale to differentiate noncoached malingerers from nonmalingerers (*d* =

1.48; see Hawes & Boccaccini, 2009). Hawes and Boccaccini (2009) also reported moderate to high effect sizes in populations where less severe impairment (*d* = 1.25) and severe impairment were feigned (*d* = 2.32). Regarding cut scores, all of the proposed cut scores from the manual are associated with moderate to high sensitivity (73T = .74; 84T = .58; 92T = .50) and moderate to high specificity (73T = .85; 84T = .89; 92T = 91; see Boccaccini & Hart, 2018).

Regarding supplemental PAI scales, the Malingering (MAL) index is comprised of eight PAI profile features (across scale and subscale scores) that are more common among individuals simulating mental illness (e.g., extremely high NIM score, extremely high Depression score plus an extremely high resistance to treatment). The presence of three or more of these features (T-score greater than 83) indicates potential malingering, while the presence of five or more of these features (T-score greater than 110) tend to be present only in profiles of individuals feigning mental illness. Meta-analytic research supports the use of MAL scores for detecting noncoached malingering (*d* = 1.15; Hawes & Boccaccini, 2009). Hawes and Boccaccini (2009) also reported moderate to large effect sizes in samples feigning less severe impairment (*d* = .90) and more severe impairment (*d* =1.89). Regarding cut scores, research has indicated that a cut score of 110T shows moderate effectiveness (sensitivity = .17, specificity = 1.00) while a cut score of 84T shows increased effectiveness (sensitivity = .51, specificity = .93; Boccaccini & Hart, 2018).

Rogers Discriminant Function (RDF) is a weighted combination of 20 PAI scales/subscales (e.g., INC, INF, Somatic Complaints, Anxiety) designed to distinguish genuine clinical patients from healthy controls simulating mental illness. T-scores greater than 59 (raw scores greater than 0) suggest malingering. Research has substantiated the effectiveness of this scale to distinguish uncoached malingerers from nonmalingerers (d = 1.13; Hawes & Boccaccini, 2009). Hawes and Boccaccini (2009) also reported moderate to high effect sizes in samples feigning moderate impairment (d = 1.23) or severe impairment (d = 2.03). One limitation of RDF is that scores perform well in simulation studies (d = 1.69), but poorly in known-group (i.e., feigning status determined by a feigning-specific criterion measure) studies (d = .31; Hawes & Boccaccini, 2009).

There are also two researcher-derived PAI scales for assessing negative distortion. The Negative Distortion Scale (NDS) consists of 15 PAI items that assess rare but genuine symptoms that differentiate genuine clinical patients from healthy controls exaggerating symptoms (Mogge et al., 2010). The researchers selected these items based on their low endorsement rate in both normative and clinical samples. Research indicates that a cutoff of 11 has strong sensitivity (.88) and adequate specificity (.62), and a cutoff of 13 provides both strong sensitivity (.85) and strong specificity (.71; Boccaccini & Hart, 2018). Additionally, other cut scores have indicated promising results (Boccaccini & Hart, 2018).

The Multiscale Feigning Index (MFI) is based on the average T-score across seven PAI clinical scales associated with feigning (Somatic, Anxiety, Anxiety-Related Disorders, Depression, Mania, Paranoia and Schizophrenia; Gaines et al., 2013). The MFI incorporates two components that researchers believe are common among feigners: symptom severity and variety of symptom endorsement. When tasked with identifying feigners on the SIRS, the MFI performed well (d = 1.60; Gaines, et al., 2013). Additionally, a cutoff of T-scores over 74 identified possible feigners (identified 76% of feigners with a specificity of 75%), while a cutoff of T-scores over 84 identified people with a high likelihood of feigning (identified 31% of feigners with a specificity of 98%; Gaines et al., 2013).

Positive Distortion

Positive distortion scores evaluate the degree to which an evaluee is attempting to present him or herself in a positive light, and potentially underreporting their symptomology. The PAI includes one validity scale created specifically to assess positive distortion. The Positive Impression Management (PIM) scale consists of items in which endorsement indicates either a very favorable impression or denies minor common shortcomings that most individuals will readily admit. The PAI manual indicates that profiles with PIM T-scores under 44 are valid, those with T-scores between 57 and 67 are moderately elevated and should be viewed with caution, and those with T-scores over 68 are elevated. Elevated scores indicate that the profile should be interpreted with caution as it is believed that the evaluee is underreporting their shortcomings. Researchers have reported strong effect sizes for the ability of scores on this subscale to identify those underreporting impairment (d = 1.47 to 1.91; Boccaccini & Hart, 2018). Regarding cut-scores, research has indicated that a cut score of 57T has strong sensitivity (.81) and strong specificity (.81), while a cut score of 68T has poor sensitivity (.41) but strong specificity (.98; Boccaccini & Hart, 2018).

Additionally, the PAI includes two supplemental scales for assessing positive distortion. The Defensiveness Index (DEF) is composed of nine profile features that tend to be observed among people who are engaging in effortful defensive responding. Similar to the MAL index, the more DEF features that are endorsed, the more defensive the evaluee's responses are presumed to be. The presence of six or more of these features (T-score greater than 70) indicates overt defensiveness. Research provides generally strong support for the ability of DEF scores to identify those underreporting impairment (d = 1.17 to 1.88), with strong sensitivity and strong specificity for the 63T cut score (sensitivity = .81, specificity = .86), and moderate sensitivity and strong specificity for the 70T cut score (sensitivity = .67. specificity = .94; Boccaccini & Hart, 2018).

Cashel Discriminant Function (CDF) scores are based on a weighted combination of six PAI scale/subscale scores (e.g., PIM, Borderline Features, Stress) to distinguish between defensive and honest responders. The PAI manual indicates that profiles with T-scores under 48 are valid, those with T-scores between 49 and 54 indicate mild defensiveness, those with T-scores between 55 and 69 are moderately elevated and should be viewed with caution, and those with T-scores over 70 are elevated. While these elevated profiles are not considered invalid, scores in this range indicate that the profile likely reflects the way that the evaluee desired to appear as opposed to how they truly present. Research has indicated moderate effect sizes for the ability of scores on CDF to differentiate between honest responders and those underreporting impairment (d = .63 to .94; Boccaccini & Hart, 2018).

Latent Profile Analysis and the PAI

Latent Profile Analysis (LPA) is a statistical modeling technique that allows researchers to sort individuals into groups (latent classes) based on observed (manifest) continuous variables. The groups (latent classes) are conceptualized as measuring underlying (latent) continuous variables. Researchers identify the best-fitting LPA model based on a comparison of fit indices [i.e., Bayesian Information Criterion (BIC), entropy of the classes, the Lo-Mendell-Ruben adjusted Likelihood Ratio Test (L-M-R LRT) and the Bootstrap Likelihood Ratio Test (BLRT)] for models with different numbers of classes. The best-fitting model will have a lower BIC value compared to alternative models, acceptable entropy (>.70), a significant L-M-R LRT, test and a significant BLRT test. The analysis also provides class probabilities for each participant in the dataset (i.e., the probability that a particular individual belongs in a proposed latent class), and researchers often use these probabilities to assign each participant to a latent class group (i.e., class with the highest probability for that participant).

In the context of response style research, LPA with PAI validity scale scores should be able to identify discrete response style classes that can then be compared on external criteria. Potential classes include normal responding, random responding, underreporting, overreporting, and general defensive responding. Comparing the groups on external criteria may show that classifying profiles as valid or invalid is an oversimplification, and that clinical scale interpretation may be improved by first placing evaluees into their appropriate response style subgroup.

Existing PAI LPA studies have focused on patterns across clinical and treatment scales. For example, Turner et al. (2008) used scores on all of clinical scales in their LPA analyses, while de Guzmán et al. (2016) focused on a subset of the clinical scales and subscales. The goals of these studies were to identify subgroups/classes of offense and personality characteristics in female sex offenders (Turner et al., 2008), and individuals receiving treatment for disordered sexual behavior based on psychological symptoms (de Guzmán et al., 2016).

Other researchers have included a combination of clinical, treatment and validity scales in their analyses. For example, Bitting (2016), Galusha (2006) and Ingram et al (2019) used scores from all 22 PAI scales, including the NIM, PIM, INF, and INC validity scales in their latent profile analyses. Overall, the profiles identified in these studies tended to reflect combinations of response style and psychopathology. Bitting (2016) used scores from sex offenders screened for Sexually Violent Predator (SVP) evaluations (see Boccaccini et al., 2010) and identified four main latent subgroups, two solely reflecting psychopathology (i.e., elevated substance use, externalizing psychopathology), one reflecting positive distortion (i.e., underreporters), and one reflecting a combination of psychopathology and negative distortion (i.e., severe psychopathology). The severe psychopathology group was marked by a significantly elevated NIM scale combined with significant elevations on select clinical scales (ARD, DEP, SCZ and BOR) and at-risk elevations on select treatment consideration scales (i.e., AGG, SUI, STR, and NON; Bitting, 2016).

Galusha (2006) used PAI clinical and INC, INF, NIM and PIM validity scores from forensic psychiatric, civil psychiatric and substance abuse patients, and also identified four main subgroups: two that reflected psychopathology (alcohol problems, depressive/borderline elevations), one that reflected normal/average individuals, and only one that reflected a combination of psychopathology and response style (negative psychopathology distortion). This latter group was marked by elevations in NIM, accompanied by elevations across nine of the clinical scales (PAR, SCZ, SOM, ANX, ARD, DEP, BOR, ANT & ALC), and all of the treatment and interpersonal scales (Galusha, 2006).

Miller et al. (2009) investigated subtypes among male and female sex offenders using the PAI clinical scales and select validity scales (i.e., NIM, PIM). They found two groups which related primarily to psychopathology (Moderate Psychopathology, Drug/Alcohol problems), one group indicative of psychopathology and response style (Extensive Psychopathology), and one group indicative of response style (Moderate Defensiveness). The Extensive Psychopathology group was marked by elevations on NIM, as well as elevations on ANX, ARD, PAR, SCZ and BOR, while Moderate Defensiveness was only marked by slight elevations in PIM.

It is important to note that the majority of these studies (Bitting, 2016; Galusha, 2006; Turner et al., 2008) eliminated invalid profiles (either based on INC, INF and/or NIM cut scores) prior to analyses. In the others (Miller et al., 2009; de Guzmán et al., 2016), it was unclear whether or not invalid profiles were included in analyses. Further, none of these studies examined LPA derived subgroups using only the PAI validity scale scores.

Response Style and Score Interpretation

Response style typologies can have implications for the predictive validity of PAI scores, specifically the clinical and treatment scales presumed to be theoretically consistent with risk assessment. Edens and Ruiz (2005; 2006) found evidence for an interaction between ANT and PIM, when predicting misconduct among male inmates. Specifically, they found that defensive responding weakened the rather strong predictive ability of the ANT scale. This interaction was corroborated when ANT was used to predict antisocial personality trait diagnoses (Boccaccini et al., 2017). This indicates that, presumably, antisocial personality disorder is associated with more modest elevations in

ANT when individuals are responding defensively (Boccaccini et al., 2017). Additionally, Gardner and Boccaccini (2017) found evidence of moderation effects of overreporting, underreporting, and disengagement. The association between ANT scores and Psychopathy Checklist-Revised (PCL-R; Hare, 2003) scores was weaker when individuals were responding indiscriminately (elevated INF) or exaggeratedly (elevated NIM and/or MAL; Gardner & Boccaccini, 2017). However, the predictive validity of ANT scores was stronger when participants were responding defensively (elevated PIM and/or DEF; Gardner & Boccaccini, 2017).

Support for the generalizability of these types of findings across samples has been mixed. Reidy et al. (2016) found limited evidence of moderating effects for PIM and NIM scores when predicting misconduct; however, they did find a main effect for PIM scores predicting misconduct, indicating that defensiveness might generally be helpful in predicting misconduct. Additionally, Boccaccini et al. (2010) investigated the utility of ANT, AGG, DOM and VPI scores to predict recidivism, and found no evidence of any moderating effect for PIM scores on predictive validity. Further, Boccaccini et al (2013) found support for the ability of NIM and PIM to predict misconduct, independently; however, they found no evidence for the interaction between response style and BOR when predicting misconduct.

PAI Predictive Validity in Risk Assessment

While the research on the interaction effects of response style is mixed, the predictive ability of the PAI in forensic samples is well supported. Gardner et al. (2015) conducted a meta-analysis investigating the utility of the most theoretically congruous PAI scales (ANT, AGG, VPI), as well as some of the lesser validated scales (DOM, WRM, BOR, DRG, ALC), when predicting misconduct, recidivism, and violence in general. Regarding institutional misconduct, scores on the ANT (d_u = .13 to 1.13, mean *d* = .39), AGG (d_u = -.03 to 1.20, mean *d* = .37), BOR (d_u = .02 to .98, mean *d* = .32), DRG (d_u = -.03 to .91, mean *d* = .28), and VPI scales (d_u = .01 to .86, mean *d* = .26) showed small to moderate support (Gardner et al., 2015). Regarding recidivism, scores on the ANT (d_u = .03 to .78, mean *d* = .31) and AGG scales (d_u = -.05 to .74, mean *d* = .23) had small to moderate support as well (Gardner et al., 2015). When predicting violent behavior, scores on the AGG (d_u = .09 to 1.59, mean *d* = .40), VPI (d_u = <.01 to .75, mean *d* = .28) and ANT scales (d_u = -.07 to 1.10, mean *d* = .26) had the most support (Gardner et al., 2015). Additionally, Gardner et al.'s (2015) results indicated stronger predictive ability in incarcerated samples, compared to treatment samples.

Boccaccini et al. (2010) examined the predictive validity of ANT, AGG, DOM and VPI regarding post release arrests in a sample of SVP evaluees. Regarding sexually violent recidivism, scores on the DOM (*d* =.23) and VPI (*d* =.21) scales showed small support and, regarding violent or sexually violent recidivism, scores on the AGG (*d* = .30) and DOM (*d* = .32) scales showed small support (Boccaccini et al., 2010). When predicting nonviolent, nonsexual recidivism, scores on the DOM (*d* = .22), VPI (*d* = .30), AGG (*d* = .34) and ANT (*d* = .37) scales showed small support as well (Boccaccini et al., 2010). Regarding violent nonsexual recidivism, scores on the ANT (*d* = .29), DOM (*d* = .32), VPI (*d* = .32) and AGG (*d* = .50) scales showed small to moderate support (Boccaccini et al., 2010). When predicting sex offender registry violations, scores on the DOM (*d* = .25), ANT (*d* = .52), VPI (*d* = .48) and AGG (*d* = .55) scales showed small to moderate support (Boccaccini et al., 2010).

Current Study

The primary goal of this study was to use Latent Profile Analysis with PAI response style measure scores to determine whether offenders can be classified into identifiable response style subgroups. I expected to identify four latent subgroups: (a) random responding, (b) overreporting, (c) underreporting and (d) honest responding. Given the potential benefits of appearing unimpaired in a post-release SVP evaluation, I expected that more offenders would be classified as underreporting than overreporting or responding randomly. A secondary goal was to examine whether response style group membership moderates the association between PAI clinical (e.g., ANT, BOR), treatment (AGG), Index (VPI) and Composite (INT, EXT) scores, and post-release recidivism. In other words, whether the predictive validity of PAI scores differed for those in different response style groups. I expected PAI scores to be stronger predictors of recidivism among honest responders than other subgroups. Among the other subgroups, I expected predictive effects to be stronger among underreporters than the other subgroups, with the scores that indicated relatively high risk in this group possibly being lower than those that indicated high risk among the honest responders (see Edens & Ruiz, 2006).

PAI scores for this study come from a sample of 1,532 male sexual offenders screened for civil commitment as Sexually Violent Predators but released because they did not meet commitment requirements. Prior research with this sample has examined univariate associations between PAI scores and recidivism (Boccaccini et al., 2010), and identified latent subgroups using the PAI validity, clinical, and treatment considerations scales (Bitting, 2016). Although these prior studies examined latent PAI subgroups and recidivism, neither attempted to identify response style subgroups and neither provided a detailed examination of the possible moderating effect of response style on recidivism. Moreover, the recidivism data I used for this study was collected more than six years after the recidivism data used in the original PAI recidivism study (Boccaccini et al., 2010), allowing for an updated examination (e.g., longer follow-up period, higher recidivism base rate) of the association between PAI scores and recidivism.

CHAPTER II

Method

Participants

Participants were male Texas Department of Criminal Justice inmates screened for civil commitment under the state's Sexually Violent Predator (SVP) statute (Texas Health & Safety Code, Title 11, Chapter 841). SVP laws allow certain states to civilly commit sexual offenders after they have served their prison sentence, if they are deemed to pose a high risk for sexual re-offense (see Miller et al., 2005). Only particular sexual offenses make offenders eligible for civil commitment, including completed or attempted contact offenses as well as aggravated kidnapping, burglary, or murder if they are deemed sexually motivated. In addition to meeting the offense requirement, offenders must further be deemed to have a "behavioral abnormality" that predisposes them to "predatory acts of sexual violence" (Texas Health & Safety Code, Title 11, Chapter 841).

During the timeframe of the evaluations for this study (1999 and 2004), 1,983 Texas offenders were screened for commitment, but not civilly committed (i.e., released; see Boccaccini et al., 2009). In a prior study with this sample, researchers found that PAI scores and post-release recidivism information were available for 1,532 (77.26%) of these offenders (Boccaccini et al., 2010). The reason PAI scores were not available for some offenders was not always clear, although correctional records indicated that 57 offenders were too mentally ill to be tested, 51 refused the evaluation, and 26 produced invalid scores (see Boccaccini et al., 2010). Earlier research with this dataset used post-release arrest data collected in 2007 (Boccaccini et al., 2009; Boccaccini et al., 2010). The dataset for the current analyses contains updated recidivism information from 2011, which has also been used to examine the predictive validity of scores from risk and psychopathy measures (Boccaccini et al., 2017b; Harris et al., 2017). For the current study, 26 of the 1,532 offenders were omitted from analyses due to the unavailability of updated post-release arrest data, leading to a final sample of 1,506. The offenders in the present sample had a mean age of release of 42.78 (*SD* = 11.98). Offenders were identified in arrest data records as White non-Hispanic (*n* = 764, 50.70%), White Hispanic (*n* = 420, 27.90%), Black (*n* = 313, 20.80%), or other/missing (*n* = 9, <1%).

Measures

Personality Assessment Inventory (PAI; Morey 1991, 2007)

The PAI is a 344-item, self-report instrument designed to assess for general personality and psychopathology, with an emphasis on clinical diagnosis and treatment planning. Each item is answered on a 4-point Likert scale (1 = *not true at all*; 2 = *slightly true*; 3 = *mainly true*; 4 = *very true*). It was normed on adults ages 18 and older and is comprised of four validity scales, 11 clinical scales, five treatment scales, and two interpersonal scales.

Validity Scales. Four scales designed to assess response style were created for the PAI: Inconsistency (INC), Infrequency (INF), Positive Impression Management (PIM) and Negative Impression Management (NIM). Additionally, four supplemental validity scales were calculated from scale and subscale scores: Malingering Index (MAL), Defensiveness Index (DEF), Cashel's Discriminant Function (CDF), and Roger's Discriminant Function (RDF). Additionally, one researcher-derived validity scale (Multiscale Feigning Index, MFI; Gaines et al, 2013) was calculated and utilized in the current analyses. No profiles were excluded from the analyses; this resulted in a combination of profiles being utilized, including those that would have been deemed invalid according to traditional classification methods.

Clinical, Treatment, and Interpersonal Scales. Eighteen additional scales were designed to assess symptomology of clinical constructs (Clinical Scales), areas of additional consideration in regard to treatment (Treatment Scales), and characteristics associated with relationships (Interpersonal Scales) to provide a comprehensive appraisal of a respondent's unique mental health. While the PAI is broadband in nature, there are particular index and composite that have proven empirically interesting in the predication of sexually violent re-offense: Antisocial Features (ANT), Aggression (AGG), Violent Potential Index (VPI), Borderline Features (BOR), Internalizing Composite (INT), and Externalizing Composite (EXT). The Internalizing (INT) and Externalizing (EXT) composite scores were developed using correctional samples (Ruiz & Edens, 2008); INT is the mean score across six scales (Anxiety, Depression, Somatic Complaints, Schizophrenia, Anxiety-Related Disorders, & Suicidal Ideation) and EXT is the mean score across seven scales (Antisocial Features, Borderline Features, Alcohol Problems, Drug Problems, Aggression, Mania, & Paranoia). Internal consistency for these scales in the PAI normative sample were good overall (.82 to .90, Morey et al., 1991, 2007). I focused my predictive analyses on these index and composite scales. Descriptive statistics for the selected validity, index and composite scales are presented in Table 1.

Table 1

Descriptive Statistics for PAI Validity, Index, and Composite T-Scores: Full Sample (n = 1,506)

Scale	Mean	SD
Validity Scales		
INC	54.27	10.04
INF	56.62	10.78
NIM	51.74	10.58
PIM	52.18	10.41
MAL	51.28	10.68
DEF	50.48	10.64
CDF	47.56	10.95
RDF	52.65	10.36
MFI	51.36	8.03
Other Scales		
AGG	48.49	9.78
ANT	56.01	8.09
BOR	53.30	10.11
VPI	54.73	12.52
INT	51.28	8.39
EXT	53.99	7.88

Post Release Arrests

The post release arrest information for this study was provided by the Texas Department of Public Safety in June 2011, representing a four-year update of the arrest data used in the earlier PAI recidivism study with this sample (Boccaccini et al., 2010 used arrest data from June 2007). Follow-up time (i.e., time between release and collection of recidivism data) for offenders in this sample ranged from 6.23 to 11.47 years (M = 8.86, SD = 1.48). The research team used National Crime Information Center offense codes to group post-release arrests into four main (nonoverlapping) recidivism categories: violent sexual (sexual; e.g., kidnapping of a minor to sexually abuse, rape, sexual assault), violent nonsexual (violent; e.g., assault, murder, robbery), nonviolent and nonsexual (e.g., probation violation, substance related charges, weapons possession), and sex offender registry violations. As of June 2011, 514 (34.10%) offenders had been arrested for a new offense: sexual (n = 61, 4.10%), violent (n = 124, 8.20%), nonviolent and nonsexual (n = 330, 21.90%) and registry violations (n = 246, 16.30%).

CHAPTER III

Results

Latent Profile Analysis

I conducted a series of LPAs with PAI validity scale scores (INC, INF, NIM, PIM, MAL, DEF, RDF, CDF, and MFI) to identify response-style subtypes. To facilitate interpretation, I converted all PAI validity scale scores into linear T-scores prior to the LPA.

I began the LPA analyses with a one-class solution and then added one additional class to each subsequent model (up to seven classes). I then compared the models using Bayesian Information Criterion (BIC), entropy, the Lo-Mendell-Ruben adjusted Likelihood Ratio Test (L-M-R LRT) and the Bootstrap Likelihood Ratio Test (BLRT) values (see Table 2). Overall, better models will have lower BIC, higher entropy, and significant L-M-R LRT and BLRT tests. BIC is the best indicator, compared to other fit indices, according to Nylund-Gibson and Masyn (2016). Using simulation studies, Nylund and Masyn (2008) determined that BIC does a better job of identifying the correct latent class model than other fit indices. Models were estimated using MPlus Version 8 (Muthén & Muthén, 1998-2017), using the Expectation-Maximization (EM) algorithm, to compute maximum likelihood estimates of the model parameters.

Table 2

Model Fit Criteria for One to Seven Class Models for PAI Validity Scales, for Models Accounting for Overlapping Item Content (Not Bolded) and Models Not Accounting for Overlapping Item Content (Bolded)

Model	Log likelihood	Number of parameters	BIC	Entropy	L-M-R LRT (*p*)	BLRT (*p*)
1 Class LPA	-49,946.804	24	100,069.222	NA	NA	NA
1 Class LPA	**-50,753.189**	**18**	**101.638.088**	**NA**	**NA**	**NA**
2 Class LPA	-49,123.689	34	98,496.162	0.949	0.0000**	0.0000**
2 Class LPA	**-49,803.410**	**28**	**99,811.702**	**0.925**	**0.0001****	**0.0000****
3 Class LPA	Not replicated	44	98,179.713	0.912	0.049*	0.0000**
3 Class LPA	**-49,275.828**	**38**	**98,829.709**	**0.866**	**0.0000****	**0.0000****
4 Class LPA	-48,783.874	54	97,962.878	0.848	0.0001**	0.0000**
4 Class LPA	**-48,845.163**	**48**	**98,041.551**	**0.851**	**0.0021***	**0.0000****
5 Class LPA	-48,647.924	64	97,764.150	0.797	0.7318	***
5 Class LPA	**-48,701.548**	**58**	**97,827.494**	**0.848**	**0.3850**	**0.0000****
6 Class LPA	-48,355.188	74	97,251.850	0.891	0.1648	0.0000**
6 Class LPA	**-48,554.833**	**68**	**97,607.236**	**0.830**	**0.5037**	**0.0000****
7 Class LPA	Not Replicated	84	97,192.741	0.879	Could not be calculated	Could not be calculated
7 Class LPA	**Not Replicated**	**78**	**97,414.920**	**0.814**	**0.6171**	**0.0000****

Note. * p <.0.05. ** p <0.001.

I expected these LPA models to violate the assumption of conditional independence as the PAI supplemental scores are often based, in part, on validity scale scores, which were also included as separate variables in the same analysis. For example, the calculation of MAL includes INF and NIM. The calculations of DEF and CDF include PIM. The calculation of RDF includes INC and INF. To address these independence concerns, I calculated one set of models accounting for the overlapping scale content and compared the fit and ease of convergence for these models to those from models without this accommodation. The models accounting for item overlap relaxed the local independence assumption by allowing the aforementioned supplemental scores to correlate (e.g., MAL with INF, MAL with NIM). When these two sets of models were compared, the models accounting for the overlapping item content did not markedly improve the model (see Table 2). Because the original models (without accommodation) were more parsimonious (i.e., fewer parameters without sacrificing fit), they were favored and utilized during the subsequent analyses.

Latent Class Enumeration

As predicted, the best-fitting model was the four-class model. Examination of the fit indices in Table 2 indicates that, relative to the models with fewer classes, the four-class model had a smaller BIC but similar entropy. Furthermore, the L-M-R LRT and the BLRT were statistically significant, indicating that this four-class solution was a better fit to the data compared to the three-class solution. Relative to the four-class model, the five-class model provided a smaller BIC value and a very similar entropy value, however it also produced a nonsignificant L-M-R LRT.

In addition, Muthén (2003) argues that substantive, as well as statistical, considerations should guide the decision on the number of classes to retain in the final model. As described more fully below, the four-class model provided more theoretically consistent yet parsimonious groups than the five-class solution. For example, there were two "honest" groups (i.e., no elevations) in the five-class solution, compared to only one "honest" group in the four-class solution. For these statistical and substantive reasons, these results indicated that the four-class model provided the best representation of the data.

Description of the Four-Class LPA Model

Class-specific means and standard deviations for the PAI scores of the four latent classes are provided in Table 3 and plotted in Figure 1. There was evidence of an Honest Responders class (*n* = 405, 26.89%) marked by the absence of notable elevations across the validity measures. There was also evidence for a Positive Impression class (*n* = 777, 51.59%) marked by moderate elevations on PIM and DEF, but not other validity scales. The third and fourth classes had more notable elevations, with the Negative Impression class (*n* = 122, 8.10%) marked by clear elevations on NIM and MFI, and the Disengagement/Inattention class (*n* = 202, 13.41%) marked by elevated INC and INF scores. The emergence of these four latent subgroups was consistent with my hypotheses. Additionally, as predicted, the Positive Impression group was the largest group.

Table 3

Class Means, Standard Deviations and Variances of Most Likely Class Membership for the Four-Class Model

	Class 1 Honest Responding	Class 2 Negative Impression	Class 3 Positive Impression	Class 4 Disengagement/ Inattention	C1 vs. C2	C1 vs. C3	C1 vs. C4	C2 vs. C3	C2 vs. C4	C3 vs. C4
PAI Validity Scale	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*d*	*d*	*d*	*d*	*d*	*d*
	n = 405	*n* = 122	*n* = 777	*n* = 202						
Inconsistency (INC)	55.03 (8.39)	58.98 (9.41)	50.02(7.81)	66.29 (9.72)	***-0.40***	***0.63***	***-1.27***	***1.11***	***-0.76***	***-1.97***
Infrequency (INF)	52.88 (8.60)	61.34 (13.61)	54.53 (8.59)	69.32 (10.26)	***-0.85***	**-0.19**	***-1.79***	***0.72***	***-0.69***	***-1.65***
Negative Impression Management (NIM)	52.04 (6.45)	78.91 (10.46)	46.91 (4.38)	53.27 (8.55)	***-3.55***	***0.99***	**-0.17**	***5.71***	***2.75***	***-1.16***
Positive Impression Management (PIM)	42.09 (6.77)	40.24 (9.86)	57.50 (6.43)	59.16 (7.14)	**0.25**	***-2.35***	***-2.48***	***-2.47***	***-2.29***	***-0.25***
Malingering Index (MAL)	51.56 (10.92)	51.15 (10.72)	51.09 (10.41)	51.53 (11.21)	0.04	0.04	0.00	0.01	-0.03	-0.04
Multiscale Feigning Index (MFI)	54.51 (5.58)	68.07 (5.54)	46.39 (4.56)	54.08 (5.40)	***-2.43***	***1.65***	0.08	***4.61***	***2.57***	***-1.62***
Defensiveness Index (DEF)	39.55 (6.63)	41.80 (8.33)	56.21 (7.55)	55.59 (7.63)	***-0.32***	***-2.30***	***-2.30***	***-1.88***	***-1.75***	0.08
Cashel Discriminant Function (CDF)	42.70 (10.57)	53.00 (13.02)	46.81 (9.31)	56.88 (9.05)	***-0.92***	***-0.42***	***-0.71***	***0.63***	***-0.36***	***-1.09***
Roger's Discriminant Function (RDF)	50.52 (9.31)	55.73 (11.88)	49.81 (7.64)	66.00 (9.67)	***-0.52***	0.08	***-1.64***	***0.71***	***-0.97***	***-2.00***

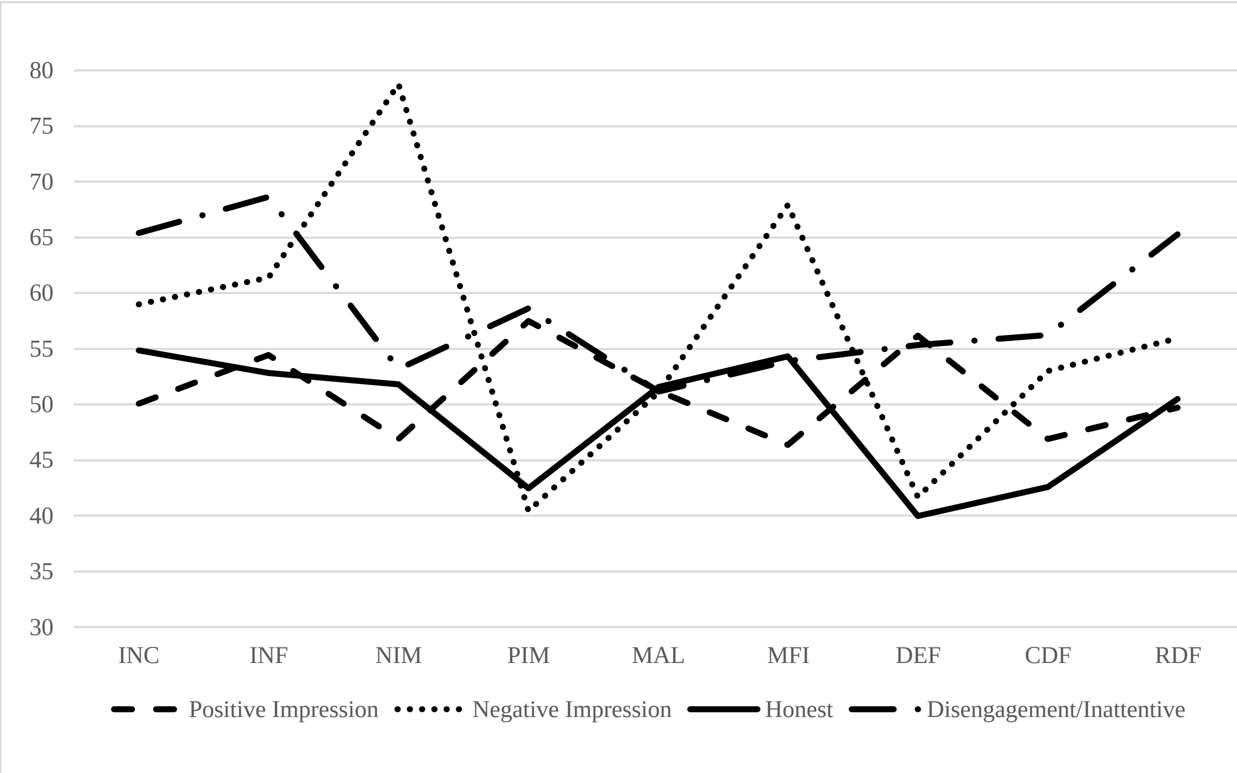
Note. Cohen's *d* values in bold are statistically significant at $p < .05$. *d* values in bold and italics are statistically significant at $p \leq .01$.

Table 3 provides mean PAI validity scale scores for offenders in each of the four response style groups, as well as Cohen's d effect size values to indicate differences between groups. There were a number of large-to-moderate sized and statistically significant differences between the groups, especially between Class 1 (Honest Responding) and Class 2 (Negative Impression; *d* = 0.25 to 3.55), and Class 3 (Positive Impression) and Class 4 (Disengagement/Inattention; *d* = 0.25 to 2.00). Specifically, the Negative Impression group scored significantly higher than honest responders on all PAI validity scales, except for PIM and MAL; honest responders scored significantly higher on PIM (*d* = 0.25) than the Negative Impression group. Additionally, responders in the Disengagement/Inattention group scored significantly higher than the Positive Impression group across almost all of the validity scales; these two groups did not differ significantly on MAL or DEF. Notably, none of the groups differed significantly on MAL (*d* = 0.00 to 0.04).

Overall, responders in the Disengagement/Inattention group scored significantly higher than all of the other groups on INC (*d* = 0.74 to 1.97), INF (*d* = 0.69 to 1.79), PIM (*d* = 0.25 to 2.48), CDF (0.36 to 1.09) and RDF (*d* = 0.97 to 2.00).

Figure 1

Profile Plot of PAI Mean Scores for the Four-Class Solution



Note. INC = Inconsistency; INF =Infrequency; NIM = Negative Impression Management; MFI = Multiscale Feigning Index; PIM = Positive Impression Management; CDF = Cashel's Discriminant Functioning.

Moderation Analyses

I used hierarchical logistic regression models to examine whether group membership significantly moderated the association between PAI predictor scale score (e.g., AGG, ANT, BOR, VPI, INT, EXT) and recidivism (violent sexual, violent nonsexual, nonviolent/nonsexual and registry violations; outcome variables). I centered all continuous predictor variables (e.g., AGG, ANT, BOR, VPI, INT, EXT) for use in the regression analyses. I conducted a separate analysis for each of these continuous predictor variables.

Positive and statistically significant regression coefficients in the regression model would indicate that those with higher levels of the trait (AGG, ANT, BOR, VPI, INT, EXT) were more likely to reoffend than those with lower levels of the trait. With respect to effect size, hierarchical logistic regression provides an odds ratio, reported as Exp(β), which, in the context of this study, provides information about how the odds of recidivism increase (an Exp(β) value greater than 1.00) or decrease (an Exp(β) value less than 1.00) with a one unit increase in the predictor variable.

For each analysis, the first regression model included only the centered PAI predictor score and outcome variables. These models examined whether there was a significant association between the PAI predictor score and recidivism in the overall sample. Table 4 provides regression results from these initial models, for each predictor. Notably, none of the PAI predictor scales predicted sexual recidivism. There were, however, significant effects for other outcome variables. AGG significantly predicted violent recidivism (Exp(β) = 1.04, $p < .001$), nonviolent/nonsexual recidivism (Exp(β) = 1.03, $p < .001$), and registry violations (Exp(β) = 1.04, $p < .001$). ANT significantly predicted violent recidivism (Exp(β) = 1.03, $p = .002$), nonviolent/nonsexual recidivism (Exp(β) = 1.04, $p < .001$), and registry violations (Exp(β) = 1.04, $p < .001$). BOR significantly predicted violent recidivism (Exp(β) = 1.03, $p = .002$), nonviolent/nonsexual recidivism (Exp(β) = 1.01, $p =.024$) and registry violations (Exp(β) = 1.03, $p < .001$). VPI significantly predicted violent recidivism (Exp(β) = 1.12, $p < .001$), nonviolent/nonsexual recidivism (Exp(β) = 1.10, $p < .001$) and registry violations (Exp(β) = 1.14, $p < .001$). INT only significantly predicted registry violations (Exp(β) = 1.03, $p < .001$). EXT significantly predicted violent recidivism (Exp(β) = 1.05, $p < .001$), nonviolent/nonsexual recidivism (Exp(β) = 1.05, $p < .001$) and registry violations (Exp(β) = 1.05, $p < .001$).

Table 4

Summary of Logistic Regression Models Examining the Association Between PAI Predictor Scales and Recidivism

	B	*SE*	*Exp(β)*	*95% CI*	*p*
			Violent Recidivism		
AGG	0.04**	0.01	1.04	1.03-1.06	<0.001
ANT	0.03*	0.01	1.03	1.01-1.05	0.002
BOR	0.03*	0.01	1.03	1.01-1.05	0.002
VPI	0.11**	0.03	1.12	1.05-1.18	<0.001
INT	0.01	0.01	1.01	0.99-1.03	0.338
EXT	0.05**	0.01	1.05	1.03-1.07	<0.001
			Sexual Recidivism		
AGG	0.01	0.01	1.01	0.98-1.03	0.630
ANT	0.00	0.12	1.00	0.97-1.03	0.856
BOR	-0.00	0.01	1.00	0.97-1.02	0.916
VPI	0.03	0.05	1.03	0.94-1.12	0.542
INT	-0.00	0.02	1.00	0.97-1.03	0.796
EXT	0.01	0.02	1.01	0.97-1.04	0.724
			Nonviolent/Nonsexual Recidivism		
AGG	0.03**	0.01	1.03	1.02-1.04	<0.001
ANT	0.04**	0.01	1.04	1.03-1.05	<0.001
BOR	0.01*	0.01	1.01	1.00-1.03	0.024
VPI	0.10**	0.02	1.10	1.06-1.15	<0.001
INT	0.01	0.01	1.01	0.99-1.02	0.435
EXT	0.05**	0.01	1.05	1.03-1.06	<0.001
			Registry Violations		
AGG	0.04**	0.01	1.04	1.03-1.06	<0.001
ANT	0.04**	0.01	1.04	1.03-1.06	<0.001
BOR	0.03**	0.01	1.03	1.02-1.05	<0.001
VPI	0.13**	0.02	1.14	1.09-1.19	<0.001
INT	0.03*	0.01	1.03	1.01-1.04	0.001
EXT	0.05**	0.01	1.05	1.04-1.07	<0.001

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

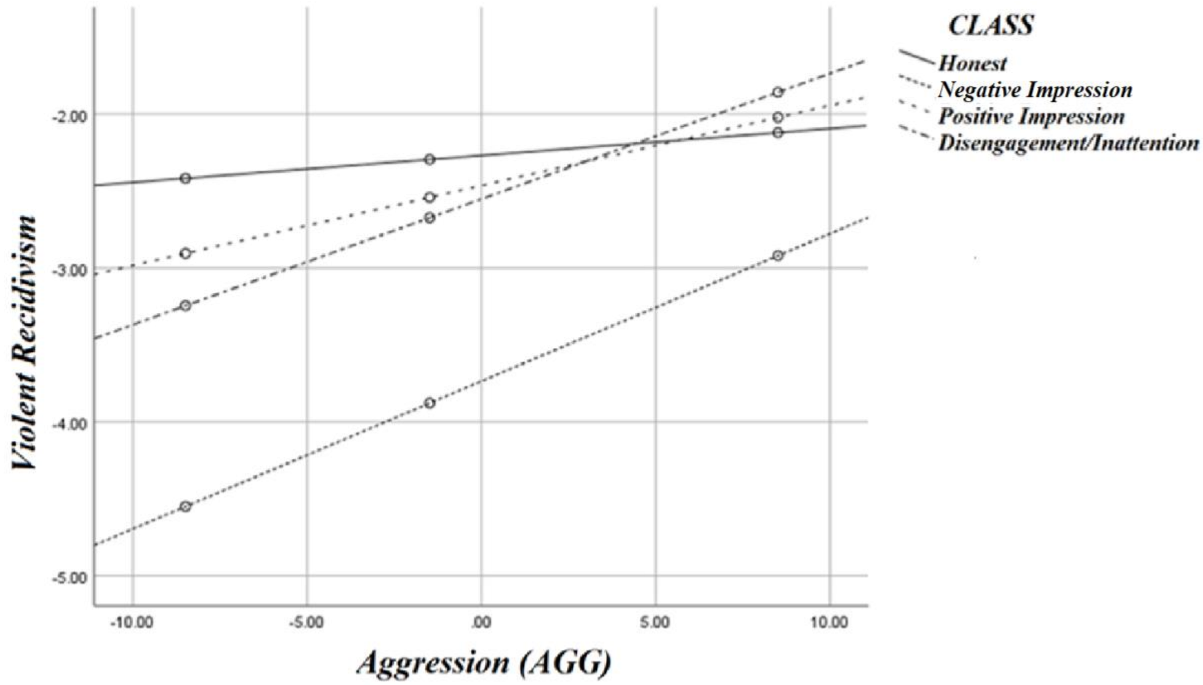
I used a second set of regression models to examine the possible moderating effect of latent class membership on the association between PAI predictor scales and recidivism. Each model included the PAI centered predictor scale score, the moderator variable (three dummy-coded variables to indicate class membership), a group of interaction terms (i.e., group membership variables multiplied by the centered predictor), and the outcome variables. For these analyses, I dummy coded the categorical classification variable using the Honest group as the reference group (DUM1 Positive Impression = 1; DUM2 Negative Impression = 1; DUM3 Disengagement/Inattention = 1). A statistically significant regression coefficient for an interaction term (or the group of terms together), would indicate a moderation effect. Detailed results from these models are provided in the Appendix (Tables 1-4).

There were five statistically significant interaction effects across the 24 models. There was one for violent recidivism, three for nonviolent/nonsexual recidivism, and one for registry violations. There was no evidence of a statistical interaction between ANT or BOR, and any type of recidivism.

The first interaction showed a smaller predictive effect for Honest responders than those in the other three subgroups (Figure 2). Specifically, there was a statistically significant interaction between AGG scores and response style group for violent recidivism. The interaction was significant for the term comparing individuals belonging to the Negative Impression group to those in the Honest Responders group [b = .0784, SE = .0342, Z = 2.295, *p* =.028] (see Figure 2). Specifically, while there was a slight positive relationship between aggression and violent recidivism for Honest responders, the association was significantly stronger for those in the Negative Impression group.

Figure 2

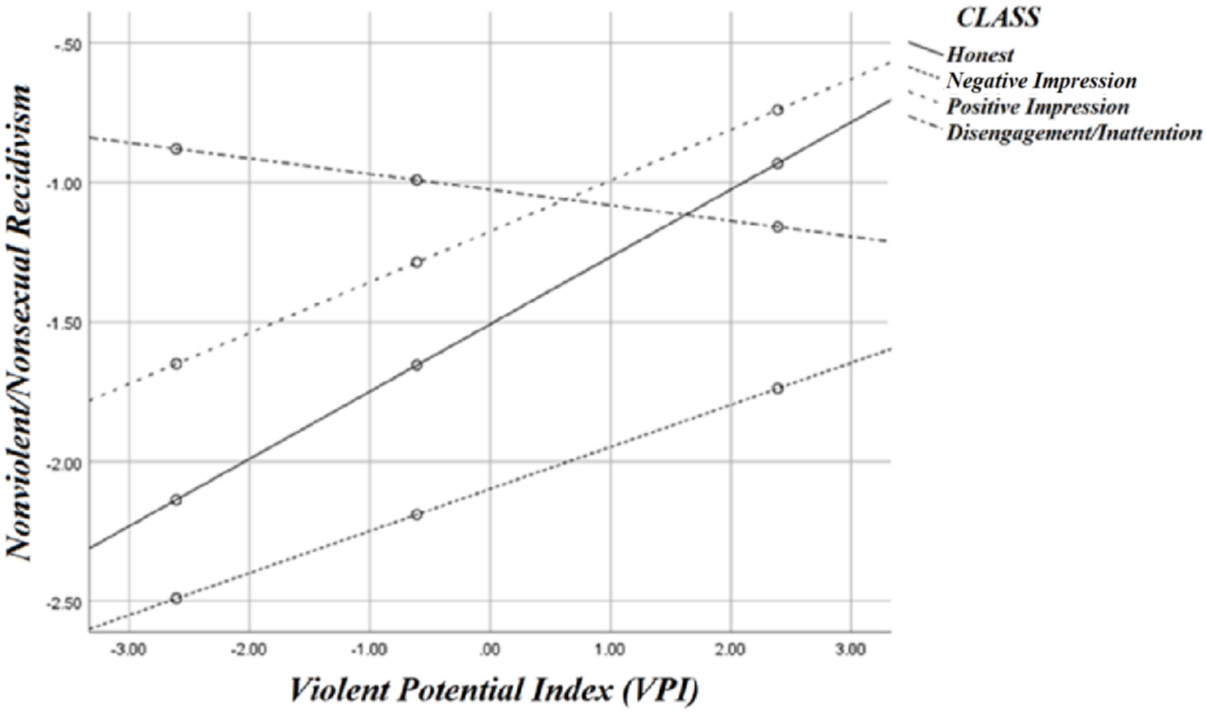
Interaction Plot of AGG Predicting Violent Recidivism



There were two interaction effects indicating weaker predictive effects for the Disengagement/Inattention group than those in the other groups (Figure 3 and Figure 4). Specifically, there was a statistically significant interaction between VPI scores and response style group for nonviolent, nonsexual recidivism (Figure 3). The interaction term was statistically significant for the dummy coded variable comparing offenders in the Honest subgroup to those in the Disengagement/Inattention group [b = -.2970, SE = .0945, Z = -3.1416, *p* = .002]. Specifically, while there was a strong positive association between VPI and nonviolent, nonsexual recidivism for those in the Honest group, there was a negative relationship for those in the Disengagement/Inattention subgroup.

Figure 3

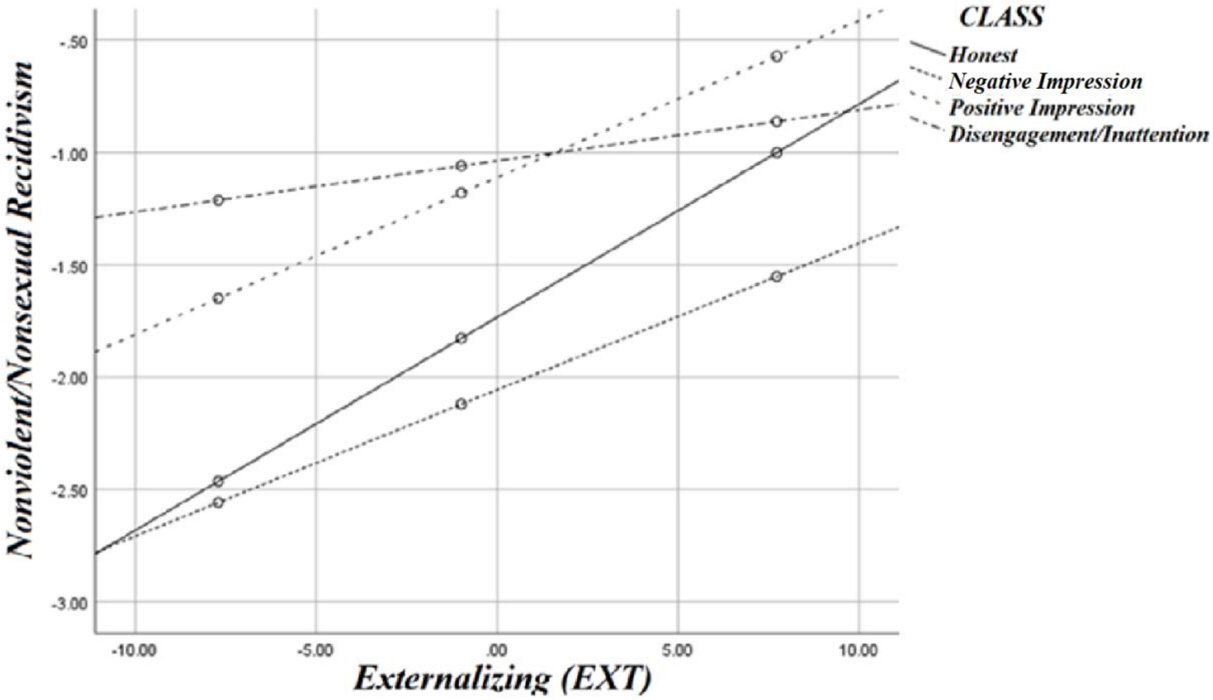
Interaction Plot of VPI Predicting Nonviolent/Nonsexual Recidivism



The second interaction indicating a weaker effect for those in the Disengagement/Inattention subgroup was for the association between EXT scores and nonviolent, nonsexual recidivism (Figure 4). Specifically, there was a statistically significant effect for the interaction term comparing the effect for Honest responders to those in the Disengagement/Inattention group [b = -.0721, SE = .0363, Z = -1.9856, *p* =.047]. While there was a clear positive relationship between EXT scores and nonviolent, nonsexual recidivism for those in the Honest responding subgroup, the positive association was significantly weaker for those in the Disengagement/Inattention group.

Figure 4

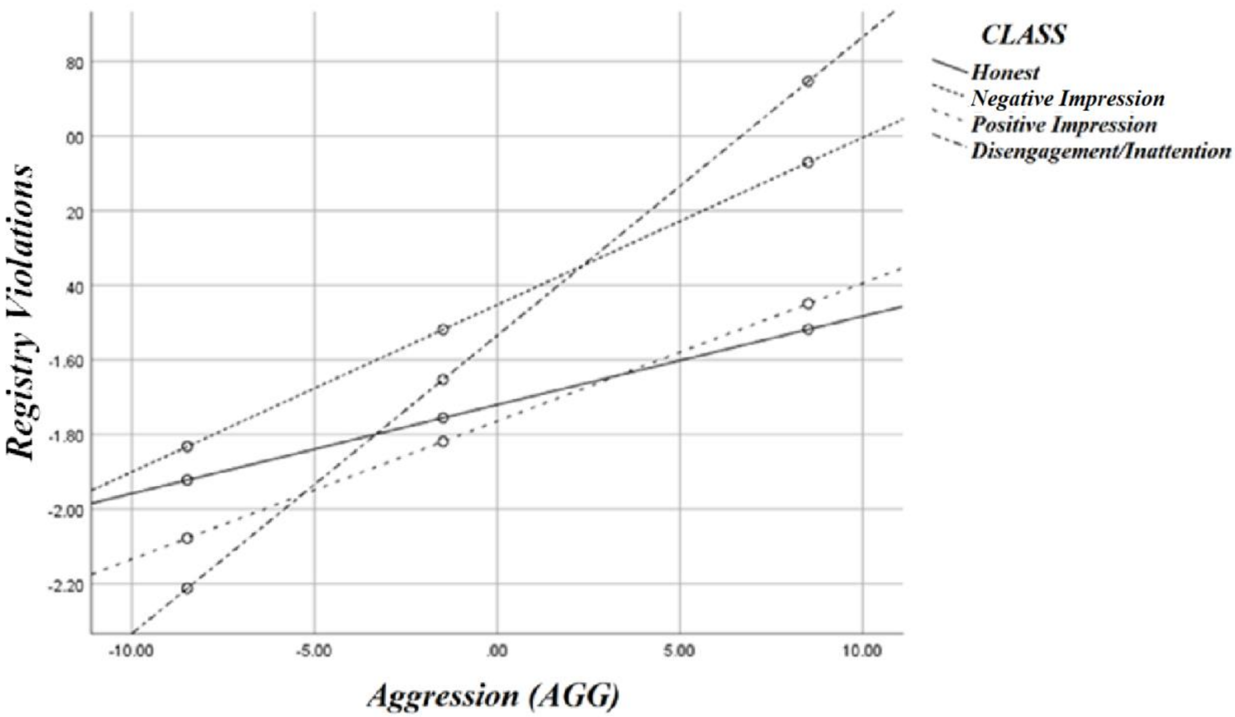
Interaction Plot of EXT Predicting Nonviolent/Nonsexual Recidivism



There was also one interaction indicating a stronger predictive effect for those in the Disengagement/Inattention subgroup. Specifically, there was a statistically significant interaction between AGG scores and response style group for predicting registry violations. The significant effect was for the dummy coded variable comparing offenders in the Honest subgroup to those in the Disengagement/Inattention group [b = .0562, SE = .0268, Z = 2.096, p =.036] (see Figure 5). Specifically, there was a notably stronger positive association between AGG scores and registry violations for those in the Disengagement/Inattention subgroup than those in the Honest subgroup.

Figure 5

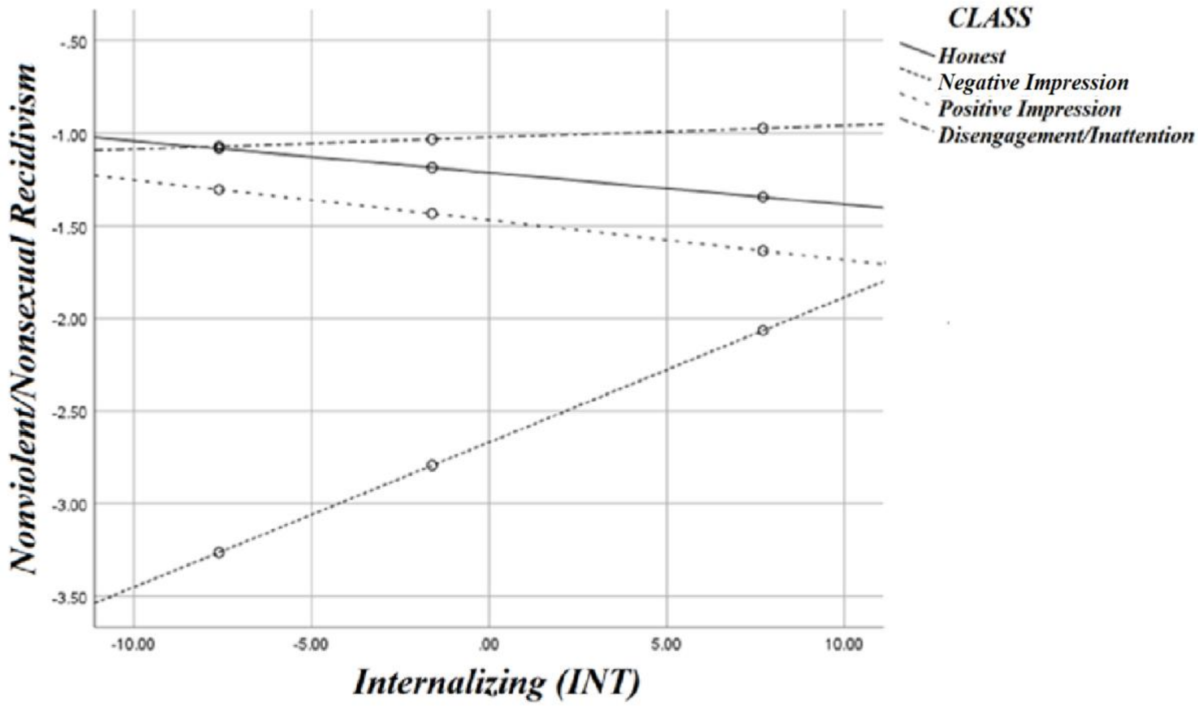
Interaction Plot of AGG Predicting Registry Violations



Finally, there was one interaction effect indicating a stronger effect for those in the Negative Impression group than those in other subgroups. Specifically, there was a statistically significant interaction effect between INT and response style subgroup for nonviolent, nonsexual recidivism (Figure 6). The interaction term was statistically significant for the dummy coded variable comparing individuals belonging to the Honest and Negative Impression subgroups [b = .0953, SE = .0366, Z = 2.6025, p = .009]. While there was a clear positive association between INT scores and recidivism for those in the Negative Impression subgroup, there was only a very slight positive association in Honest responders and a negative association for the two other subgroups.

Figure 6

Interaction Plot of INT Predicting Nonviolent/Nonsexual Recidivism



CHAPTER IV

Discussion

While measures exist to specifically measure malingering, the majority of forensic evaluators prefer multiscale inventories with imbedded validity scales (Borum & Grisso, 1995; McLaughlin & Kan, 2014). The PAI is a broadband, multi-scale inventory with a wealth of research providing support for the predictive ability of its clinical scales (Boccaccini et al., 2010; Gardner et al., 2015). The PAI also has 11 scales designed to aid in response-style interpretation, as well as clinical, treatment, and interpersonal scales, making it a valuable forensic measure.

Assessing for response style is particularly relevant in forensic cases, due to the inherent, external motivation to distort (see Otto, 2002). Historically, validity scores serve to weed out uninterpretable profiles, with the premise that invalid scores on validity scales impact the real-world predictability of clinical scales. However, this assertion rests on the assumption that the embedded validity scales of the PAI delineate real-world response style groups, and these groups will impact the predictive validity of the non-validity scales.

Response-Style Groups

Existing PAI LPA studies have focused on patterns across clinical and treatment scales (Turner et al., 2008; de Guzmán et al., 2016), clinical, treatment, and validity scales (Galusha, 2006; Bitting, 2016; Ingram et al., 2019), and clinical and validity scales (Miller et al., 2009). Those that incorporated validity scales in their analyses generally found groups that reflected combinations of response style and psychopathology; however, some found evidence for distinct response style groups, primarily positive distortion and honest responding. Although these prior studies examined latent PAI subgroups, none have attempted to identify subgroups on the PAI utilizing only response-style scales.

The findings from this study are consistent with four theoretically congruous response styles: Honest responders, Positive Impression management, Negative Impression management and Disengagement/Inattention. Overall, the findings from this study lend real-world support to theoretical response styles. They also not only lend support to the response style scales of the PAI, but also the response style scales of numerous other measures. However, the findings of this study also indicate that some scales are more effective than others for identifying response style subtypes. For example, none of the latent groups differed on MAL, suggesting that scores on this measure may capture aspects of multiple response style domains.

PAI's Predictive Validity

Research has identified several PAI scales that are associated with future misconduct and recidivism: ANT, AGG, VPI, DOM, WRM, BOR, DRG, and ALC (Boccaccini et al., 2010; Gardner et al., 2015). Specifically, ANT, AGG, VPI and BOR have shown small to moderate predictive power when predicting most types of recidivism, including violent recidivism, sexual recidivism, general recidivism, and institutional recidivism/registry violations. Additionally, two other PAI scales are of potential interest, as they were derived using correctional samples: INT and EXT. Prior research (Ruiz & Edens, 2008; Boccaccini et al., 2013) found that EXT was associated with instructional misconduct, while INT was negatively associated with general misconduct.

Overall, results from the current study are consistent with prior studies with respect to predicting violent recidivism, general recidivism, and registry violations. For example, AGG, ANT, BOR and VPI significantly predicted violent recidivism, general recidivism, and registry violations. Additionally, EXT significantly predicted violent recidivism, general recidivism, and registry violations, while INT significantly predicted registry violations.

On the other hand, there was less support for the prediction of sexual recidivism. However, this finding is not inconsistent with sexual recidivism research. Regarding the predictive ability of the PAI, only DOM and VPI have shown a significant predictive ability, and this effect was small (Boccaccini et al., 2010). More broadly, research has identified numerous variables (i.e., sexual deviance, treatment noncompliance, history of sexual offenses, age of first sexual offense, antisocial personality disorder, number of prior offenses) which load onto two main factors associated with sexual recidivism (sexual deviance and antisocial beliefs/orientation; Hanson & Bussière, 1998; Quinsey et al., 1995; Roberts et al., 2002). While none of the PAI clinical scales selected for inclusion in this study significantly predicted sexual recidivism, none of these scales measure the aforementioned topics known to be predictive of sexual offending. It is also important to consider that this might be impacted by the underrepresentation of this type of recidivism in this sample. Of the 514 offenders who reoffended in this sample, only 61 committed violent, sexual offenses, which represents less than 5% of the total sample.

Moderation Analyses

Another goal of the current study was to investigate whether the predictive validity of PAI scores depends on response style. Prior research has come to mixed conclusions about this issue (Piedmont et al., 2000; Edens & Ruiz, 2005, 2006; Reidy et al., 2016; Gardner & Boccaccini, 2017), with some finding a moderating effect of response style (i.e., INF, NIM, MAL, PIM, DEF) on the relationship between ANT and PCL-R scores.

Overall, results from the current study do not lend strong support for a consistent moderating effect of response style on predictive validity. Across the 24 moderation models in this study, only five were statistically significant. In other words, for 19 of the 24 analyses, there was no evidence that the strength of the association between a PAI scale and a recidivism variable differed depending on response style; the predictive effect was similar for those in the Honest, Positive Impression, Negative Impression, and Disengagement/Inattention subgroups.

For some variables, the predictive effect was in the same direction for all groups, but stronger for one group in particular. For example, while there was a slightly positive relationship between AGG and violent recidivism across all four response style groups, this association was significantly stronger in the Negative Impression group. Similarly, while there was a positive relationship between EXT and nonviolent, nonsexual recidivism, this relationship was significantly stronger in the Disengagement/Inattention group. Additionally, the positive relationship between AGG and registry violations was significantly stronger in the Disengagement/Inattention group, compared to the positive relationship for the other groups. For other variables, the predictive effect for one response style group (or multiple groups) was in the opposite direction. For example, while there was a positive relationship between VPI and nonviolent, nonsexual recidivism for three of the response style groups, this relationship was negative in the Disengagement/Inattention group. Relatedly, Negative Impression group membership was associated with a strong positive association between INT symptomology and nonviolent, nonsexual recidivism, while the other response style groups were associated with either a negative relationship, or a very slight positive relationship.

Overall, the results from the current study do not lend support to the moderating effect of response style, indicating that the concern which drives some of the cut-score justification might not be as warranted as previously believed. However, this is the first analysis investigating response style in this way, so additional studies examining this relationship would need to be conducted to validate the generalizability of these results.

Limitations and Future Directions

One limitation of the current study is that the latent groups were created using a combination of respondents who would be considered valid and invalid by the traditional cut-score approach. In the current study, the mean scores for each of the response groups (i.e., NIM for Negative Impression, PIM for Positive Impression, and INC and INF for Disengagement/Inattention) were moderately elevated, indicating that their profiles should be viewed with caution; none of these average validity scale scores were elevated to the point of invalidation, and only one (RDF) was elevated to the point of suggesting malingering. Overall, this likely indicates that the response style subgroups generated were a combination of valid and invalid profiles (according to traditional classification methods). From a theoretical perspective, this approach allowed for the inclusion of profiles across the response spectrum, facilitating a detailed picture of naturally occurring response style groups. However, given that some of the profiles included in these analyses would not have been interpreted using traditional approaches, it is unclear if these response style groups would exist in a real-world scenario after invalid profiles were eliminated. Future studies could investigate whether these validity-scale latent profiles replicate in a sample of valid profiles. It is also possible that the latent groups generated are reflecting a combination of genuine psychopathology and response style, specifically the Negative Impression group. Research has indicated NIM scores are generally higher in clinical populations, compared to community populations, and correlate with many PAI clinical scales (Hopwood et al., 2007). These findings suggest that elevated, though not invalid, NIM scores might be a reflection of genuine psychopathology, as opposed to feigned impairment. In this sample, while the Negative Impression group had the highest NIM mean score among the groups, it was not elevated to the point of invalidation. This indicates that perhaps this group was capturing response style and genuine psychopathology.

Conclusion

Consistent with a vast body of research, the present study suggests that four theoretically congruous response styles exist in a real-world sample of offenders: Honest responders, Positive Impression management, Negative Impression management and Disengagement/Inattention. Further, it lends support to the utility of, most, the PAI validity scales to delineate these response styles. Further, the results from this study support the existing literature regarding the predictive utility of the PAI scales when predicting violent recidivism, general recidivism, and registry violations. Specifically, the results from this study lend strong support for AGG, ANT, BOR, VPI, EXT and INT. Conventional cut-score interpretation of the PAI presumes a strong, although virtually untested, moderating effect of response style on the association between substantive clinical scales and outcomes. However, support for this presumption was minimally supported by the results from this study. Three models indicated response style membership strengthened the scale-recidivism associations, while two of the models indicated response style group membership weakened, or changed the direction of, the relationship between scale score and recidivism. These results might indicate that the concern which drives some of the rationale for the traditional cut-score procedure might not be as justified as previously believed, however, this conclusion is made cautiously as this is the first analysis investigating response style in this way.

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APPENDIX

Table 1

Logistical Regression Results Examining the Potential Moderating Effect of Response Style Classification on the Association Between Violent Recidivism and PAI Scales

PAI scales	B	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Violent Recidivism (Model $R^2 = .022$, $p < .001$[1]) (Block $R^2 = .017$, $p < .001$)						
AGG	.017	.016	[.99, 1.05]	1.70	.28	1.02
Positive Impression	-1.47	.71	[-.06, .92]	4.29	.04	.23
Negative Impression	-.20	.24	[.52, 1.31]	.67	.41	.82
Disengagement/Inattention	-.28	.35	[.38, 1.50]	.66	.42	.74
Positive Impression x AGG	.08	.03	[1.01, 1.16]	1.27	.02	1.08
Negative Impression x AGG	.03	.02	[.99, 1.08]	2.14	.14	1.04
Disengagement/Inattention x AGG	.06	.04	[1.00, 1.14]	3.44	.06	1.07
Violent Recidivism (Model $R^2 = .01$, $p = .07$) (Block $R^2 = .007$, $p = .033$)						
ANT	.01	.02	[.97, 1.05]	.30	.58	1.01
Positive Impression	-.82	.56	[.15, 1.32]	2.15	.14	.44
Negative Impression	-.31	.24	[.46, 1.16]	1.73	.19	.73
Disengagement/Inattention	-.12	.31	[.49, 1.63]	.14	.71	.89
Positive Impression x ANT	.05	.03	[.99, 1.11]	2.37	.12	1.05
Negative Impression x ANT	.02	.03	[.97, 1.08]	.45	.50	1.02
Disengagement/Inattention x ANT	.01	.04	[.94, 1.10]	.12	.73	1.01
Violent Recidivism (Model $R^2 = .01$, $p = .07$) (Block $R^2 = .007$, $p = .030$)						
BOR	.01	.02	[.97, 1.06]	.36	.57	1.01
Positive Impression	-1.29	.77	[.06, 1.23]	2.87	.09	.27
Negative Impression	-.13	.29	[.50, 1.54]	.21	.65	.88
Disengagement/Inattention	-.09	.34	[.47, 1.78]	.07	.80	.92

(continued)

[1] Cox & Snell

PAI scales	B	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Positive Impression x BOR	.06	.04	[.98, 1.14]	2.36	.12	1.06
Negative Impression x BOR	.03	.03	[.96, 1.09]	.62	.43	1.03
Disengagement/Inattention x BOR	.04	.04	[.94, 1.09]	.08	.78	1.01
Violent Recidivism (Model R^2 = .01, *p* = .15) (Block R^2 = .003, *p* < .310)						
INT	-.03	.03	[.92, 1.02]	1.20	2.73	.97
Positive Impression	-1.28	.90	[.05, 1.62]	2.03	.16	.28
Negative Impression	-.80	.32	[.25, .82]	6.85	.01	.45
Disengagement/Inattention	-.32	.33	[.38, 1.40]	.90	.34	.73
Positive Impression x INT	.09	.05	[1.00, 1.21]	3.46	.06	1.10
Negative Impression x INT	-.02	.04	[.90, 1.07]	.21	.64	.98
Disengagement/Inattention x INT	.06	.05	.96, 1.18]	1.52	.22	1.06
Violent Recidivism (Model R^2 = .02, *p* = .002) (Block R^2 = .014, *p* < .001)						
EXT	.04	.02	[1.00, 1.09]	3.19	.07	1.04
Positive Impression	-.97	.68	[.10, 1.44]	2.04	.15	.38
Negative Impression	-.02	.26	[.59, 1.62]	.01	.93	.98
Disengagement/Inattention	-.06	.34	[.48, 1.85]	.03	.87	.95
Positive Impression x EXT	.04	.04	[.96, 1.13]	.86	.36	1.04
Negative Impression x EXT	.03	.03	[.96, 1.10]	.73	.39	1.03
Disengagement/Inattention x EXT	.02	.05	[.92, 1.13]	.10	.76	1.12
Violent Recidivism (Model R^2 = .01 *p* = .01) (Block R^2 = .012, *p* = .002)						
VPI	.10	.07	[.97, 1.26]	2.40	.12	1.11
Positive Impression	-1.33	.74	[.06, 1.14]	3.19	.07	.27
Negative Impression	-.17	.24	[.53, 1.34]	.53	.47	.84
Disengagement/Inattention	-.04	.31	[.53, 1.75]	.02	.89	.96
Positive Impression x VPI	.11	.11	.90, 1.39]	1.07	.30	1.12
Negative Impression x VPI	.08	.10	[.98, 1.32]	.71	.40	1.09
Disengagement/Inattention x VPI	-.01	.12	[.78, 1.26]	.01	.94	.99

Note. *n* = 1,506.

Table 2
Logistical Regression Results Examining the Potential Moderating Effect of Response Style Classification on the Association Between Nonviolent Recidivism and PAI Scales

PAI scales	B	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Nonviolent Recidivism (Model $R^2 = .019$, $p < .001$[2]) (Block $R^2 = .017$, $p < .001$)						
AGG	.04	.01	[1.02, 1.07]	10.44	.00	1.04
Positive Impression	-.55	.40	[.26, 1.27]	1.86	.17	.58
Negative Impression	.19	.17	[.86, 1.71]	1.24	.27	1.21
Disengagement/Inattention	.44	.22	[1.01, 2.37]	4.10	.04	1.55
Positive Impression x AGG	.02	.02	[.98, 1.07]	.99	.32	1.02
Negative Impression x AGG	-.02	.02	[.95, 1.02]	1.19	.28	.98
Disengagement/Inattention x AGG	-.01	.02	[.94, 1.03]	.34	.56	.99
Nonviolent Recidivism (Model $R^2 = .03$, $p < .001$) (Block $R^2 = .026$, $p < .001$)						
ANT	.05	.01	[1.02, 1.08]	11.06	.00	1.05
Positive Impression	-.88	.45	[.17, 1.00]	3.88	.05	.42
Negative Impression	.24	.17	[.91, 1.78]	1.98	.16	1.27
Disengagement/Inattention	.46	.21	[1.04, 2.39]	4.58	.03	1.58
Positive Impression x ANT	.04	.03	[.99, 1.10]	2.03	.15	1.04
Negative Impression x ANT	-.00	.02	[.96, 1.04]	.00	.96	1.00
Disengagement/Inattention x ANT	-.04	.03	[.92, 1.02]	1.66	.20	.97
Nonviolent Recidivism (Model $R^2 = .01$, $p = .04$) (Block $R^2 = .006$, $p = .055$)						
BOR	.02	.02	[.99, 1.05]	1.74	.19	1.02
Positive Impression	-.84	.52	[.16, 1.20]	2.60	.11	.43
Negative Impression	.18	.20	[.80, 1.79]	.78	.38	1.20
Disengagement/Inattention	.41	.23	[.96, 2.35]	3.20	.07	1.50
Positive Impression x BOR	.04	.03	[.98, 1.10]	1.75	.19	1.04
Negative Impression x BOR	.00	.02	[.96, 1.05]	.01	.94	1.00
Negative Impression x BOR	-.04	.03	[.92, 1.02]	1.80	.18	.97

(continued)

[2] Cox & Snell

PAI scales	B	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Nonviolent Recidivism (Model $R^2 = .04$, $p < .001$) (Block $R^2 = .002$, $p = .454$)						
INT	-.02	.02	[.95, 1.02]	.74	.39	.98
Positive Impression	-.32	.47	[.29, 1.83]	.47	.50	.72
Negative Impression	.62	.19	[1.27, 2.72]	.19	.00	1.86
Disengagement/Inattention	.70	.23	[1.27, 3.17]	.23	.00	2.01
Positive Impression x INT	-.03	.03	[.91, 1.04]	.03	.37	.97
Negative Impression x INT	-.03	.02	[.93, 1.02]	.02	.30	.98
Disengagement/Inattention x INT	-.07	.04	[.87, 1.00]	.04	.05	.93
Nonviolent Recidivism (Model $R^2 = .01$, $p = .09$) (Block $R^2 = .036$, $p < .001$)						
EXT	.10	.02	[1.06, 1.14]	26.08	.00	1.10
Positive Impression	-1.45	.66	[.07, .84]	4.93	.03	.23
Negative Impression	-.26	.20	[.53, 1.14]	1.72	.19	.78
Disengagement/Inattention	.19	.22	[.79, 1.86]	.76	.38	1.21
Positive Impression x EXT	.10	.04	[1.02, 1.18]	6.77	.01	1.10
Negative Impression x EXT	-.00	.03	[.94, 1.05]	.02	.88	.97
Disengagement/Inattention x EXT	.02	.03	[.96, 1.10]	.47	.50	1.02
Nonviolent Recidivism (Model $R^2 = .03$, $p < .001$) (Block $R^2 = .022$, $p < .001$)						
VPI	.24	.05	[1.15, 1.41]	22.73	.00	1.27
Positive Impression	-.59	.48	[.22, 1.43]	1.49	.22	.55
Negative Impression	.33	.17	[.99, 1.96]	3.71	.05	1.40
Disengagement/Inattention	.48	.21	[1.06, 2.46]	5.06	.02	1.62
Positive Impression x VPI	-.09	.08	[.78, 1.07]	1.21	.27	.91
Negative Impression x VPI	-.06	.07	[.82, 1.09]	.66	.42	.94
Disengagement/Inattention x VPI	-.30	.10	[.62, .89]	9.87	.00	.74

Note. $n = 1,506$

Table 3
Logistical Regression Results Examining the Potential Moderating Effect of Response Style Classification on the Association Between Sexual Recidivism and PAI Scales

PAI scales	*b*	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Sexual Recidivism (Model $R^2 = .004$, $p = .53$[3]) (Block $R^2 = .002$, $p = .685$)						
AGG	-.02	.03	[.92, 1.03]	.67	.41	.98
Positive Impression	.31	.62	[.40, 4.63]	.25	.62	1.37
Negative Impression	.33	.33	[.72, 2.65]	.96	.33	1.38
Disengagement/Inattention	-.23	.50	[.30, 2.11]	.21	.64	.79
Positive Impression x AGG	.02	.05	[.94, 1.11]	.24	.63	1.02
Negative Impression x AGG	.07	.04	[1.00, 1.15]	3.37	.07	1.07
Disengagement/Inattention x AGG	.02	.06	[.90, 1.15]	.08	.78	1.02
Sexual Recidivism (Model $R^2 = .004$, $p = .61$) (Block $R^2 = .001$, $p = .772$)						
ANT	-.03	.03	[.91, 1.04]	.60	.44	.97
Positive Impression	.45	.60	[.48, 5.14]	.57	.45	1.58
Negative Impression	.31	.33	[.72, 2.61]	.90	.34	1.37
Disengagement/Inattention	-.24	.51	[.29, 2.12]	.23	.63	.78
Positive Impression x ANT	.01	.05	[.92, 1.11]	.05	.83	1.01
Negative Impression x ANT	.07	.04	[.99, 1.16]	2.56	.11	1.07
Disengagement/Inattention x ANT	-.01	.07	[.86, 1.15]	.01	.92	.99
Sexual Recidivism (Model $R^2 = .002$, $p = .82$) (Block $R^2 = .001$, $p = .784$)						
BOR	-.04	.04	[.89, 1.04]	.88	.35	.97
Positive Impression	.04	.92	[.17, 6.31]	.00	.96	1.04
Negative Impression	.18	.40	[.55, 2.63]	.20	.65	1.20
Disengagement/Inattention	-.44	.56	[.22, 1.91]	.63	.43	.64
Positive Impression x BOR	.04	.06	[.93, 1.17]	.57	.45	1.05
Negative Impression x BOR	.05	.05	[.96, 1.16]	1.25	.27	1.06
Disengagement/Inattention x BOR	.08	.07	[.95, 1.24]	1.41	.24	1.08

(continued)

[3] Cox & Snell

PAI scales	*b*	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Sexual Recidivism (Model R^2 = .002, *p* = .89) (Block R^2 = .001, *p* = .794)						
INT	-.05	.05	[.87, 1.05]	.89	.35	.96
Positive Impression	-.06	1.16	[.10, 9.21]	.00	.96	.94
Negative Impression	.20	.39	[.57, 2.61]	.27	.60	1.22
Disengagement/Inattention	-.37	.56	[.23, 2.06]	.45	.51	.69
Positive Impression x INT	.06	.07	[.92, 1.23]	.70	.40	1.06
Negative Impression x INT	.05	.06	[.93, 1.19]	.71	.40	1.05
Disengagement/Inattention x INT	.08	.08	[.92, 1.28]	.91	.34	1.08
Sexual Recidivism (Model R^2 = .004, *p* = .62) (Block R^2 = .001, *p* = .696)						
EXT	-.03	.04	[.98, 1.05]	.60	.44	.97
Positive Impression	.44	.77	[.34, 7.07]	.33	.57	1.56
Negative Impression	.34	.35	[.71, 2.79]	.98	.32	1.41
Disengagement/Inattention	-.30	.53	[.27, 2.09]	.32	.57	.74
Positive Impression x EXT	.02	.07	[.89, 1.16]	.06	.80	1.02
Negative Impression x EXT	.08	.05	[.98, 1.20]	2.59	11	1.09
Disengagement/Inattention x EXT	.06	.09	[.89, 1.27]	.42	.52	1.06
Sexual Recidivism (Model R^2 = .004, *p* = .57) (Block R^2 = .001, *p* = .693)						
VPI	-.01	.12	[.789, 1.25]	.01	.94	.99
Positive Impression	.57	.83	[.35, 9.07]	.47	.49	1.78
Negative Impression	.43	.34	[.80, 2.97]	1.66	.20	1.54
Disengagement/Inattention	-.24	.54	[.28, 2.24]	.21	.65	.78
Positive Impression x VPI	-.03	.18	[.69, 1.37]	.03	.86	.97
Negative Impression x VPI	.19	.15	[.90, 1.61]	1.63	.20	1.21
Disengagement/Inattention x VPI	-.14	.27	[.51, 1.48]	.28	.60	.87

Note. *n* = 1,506

Table 4

Logistical Regression Results Examining the Potential Moderating Effect of Response Style Classification on the Association Between Registry Violations and PAI Scales

PAI Scales	*b*	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Registry Violations (Model R^2 = .03, p < .001[4]) (Block R^2 = .026, p < .001)						
AGG	.02	.01	[1.00, 1.05]	3.29	.07	1.02
Positive Impression	.27	.35	[.66, 2.60]	.59	.44	1.31
Negative Impression	-.04	.19	[.66, 1.39]	.05	.82	.96
Disengagement/Inattention	.19	.25	[.74, 1.96]	.56	.45	1.21
Positive Impression x AGG	.02	.02	[.98, 1.07]	.90	.34	1.02
Negative Impression x AGG	.01	.02	[.98, 1.05]	.49	.49	1.01
Disengagement/Inattention x AGG	.06	.03	[1.00, 1.12]	4.39	.04	1.06
Registry Violations (Model R^2 = .03, p < .001) (Block R^2 = .023, p < .001)						
ANT	.03	.02	[1.00, 1.06]	4.25	.04	1.03
Positive Impression	.57	.33	[.94, 3.36]	3.09	.08	1.77
Negative Impression	-.03	.19	[.67, 1.41]	.02	.88	.97
Disengagement/Inattention	.36	.23	[.90, 2.25]	2.33	.13	1.43
Positive Impression x ANT	-.01	.02	[.95, 1.04]	.17	.68	.99
Negative Impression x ANT	.02	.02	[.98, 1.06]	.85	.36	1.02
Disengagement/Inattention x ANT	-.01	.03	[.93, 1.05]	21	.65	.99
Registry Violations (Model R^2 = .02, p < .001) (Block R^2 = .018, p < .001)						
BOR	.02	.02	[.98, 1.05]	1.05	.31	1.02
Positive Impression	.46	.45	[.65, 3.85]	1.03	.31	1.58
Negative Impression	-.01	.23	[.63, 1.55]	.00	.96	.99
Disengagement/Inattention	.28	.26	[.80, 2.20]	1.20	.27	1.33
Positive Impression x BOR	.00	.03	[.95, 1.06]	.01	.92	1.00
Negative Impression x BOR	.01	.03	[.96, 1.06]	.15	.70	1.01
Disengagement/Inattention x BOR	.03	.03	[.97, 1.09]	.83	.36	1.03

(continued)

[4] Cox & Snell

PAI Scales	*b*	*SE*	95% CI of *b*	*Wald*	*p*	*Exp(B)*
Registry Violations (Model $R^2 = .02$, $p < .001$) (Block $R^2 = .013$, $p < .001$)						
INT	-.02	.02	[.94, 1.02]	1.16	.28	.98
Positive Impression	.12	.56	[.38, 3.36]	.04	.84	1.12
Negative Impression	-.49	.23	[.39, .96]	4.67	.03	.61
Disengagement/Inattention	.02	.25	[.63, 1.67]	.01	.93	1.02
Positive Impression x INT	.05	.04	[.98, 1.13]	2.16	.14	1.05
Negative Impression x INT	.00	.03	[.94, 1.07]	.00	.99	1.00
Disengagement/Inattention x INT	.07	.04	[1.00, 1.16]	3.78	.05	1.08
Registry Violations (Model $R^2 = .03$, $p < .001$) (Block $R^2 = .027$, $p < .001$)						
EXT	.05	.02	[1.02, 1.10]	7.97	.01	1.06
Positive Impression	.70	.40	[.92, 4.42]	3.04	.08	2.01
Negative Impression	.18	.21	[.80, 1.78]	.72	.40	1.19
Disengagement/Inattention	.38	.26	[.89, 2.41]	2.21	.14	1.46
Positive Impression x EXT	-.03	.03	[.91, 1.03]	1.21	.27	.97
Negative Impression x EXT	.01	.03	[.96, 1.06]	.14	.70	1.01
Disengagement/Inattention x EXT	.01	.04	[.93, 1.09]	.05	.83	1.01
Registry Violations (Model $R^2 = .02$, $p < .001$) (Block $R^2 = .022$, $p < .001$)						
VPI	.13	.05	[1.03, 1.27]	6.09	.01	1.14
Positive Impression	.28	.43	[.57, 3.07]	.41	.52	1.32
Negative Impression	-.01	.19	[.68, 1.43]	.00	.95	.99
Disengagement/Inattention	.36	.23	[.91, 2.24]	2.46	.12	1.43
Positive Impression x VPI	-.04	.08	[.82, 1.13]	.22	.64	.96
Negative Impression x VPI	.03	.08	[.88, 1.21]	.16	.69	1.03
Disengagement/Inattention x VPI	-.09	.10	[.76, 1.11]	.85	.36	.92

Note. $n = 1,506$

VITA

ELLEN E. REINHARD, M.A.

EDUCATION

Anticipated completion 2022 — **Doctor of Philosophy (Clinical Psychology, Forensic Emphasis)**
Sam Houston State University
Dissertation: Using Latent Profile Analysis to Identify Response Style Subgroups on the Personality Assessment Inventory (PAI): Implications for Predictive Validity
Chair: Marcus Boccaccini, Ph.D.

2021-Present — **Doctoral Internship**
Office of Mental Health Services/Western State Hospital
Lakewood, WA
Rotations: (1) Competency Evaluation, (2) Juvenile Forensic Evaluation, & (3) Competency Restoration Treatment
Directors: Marilyn A. Ronnei, Ph.D. and Richard W. Yocum, Ph.D.

2016 — **Master of Arts (Forensic Psychology)**
John Jay College of Criminal Justice
Thesis: Psychopathy, Empathy and Helping Behavior
Chair: Diana M. Falkenbach, Ph.D.

2012 — **Bachelor of Arts (Neuroscience)**
Drew University

CLINICAL EXPERIENCE

April 2022-July 2022 — **Doctoral Intern, Competency Restoration Treatment rotation**
Fort Steilacoom Competency Restoration Program
Lakewood, WA

Responsibilities:
- Observe and co-lead court-ordered, competency restoration groups
- Co-author admission and treatment plan notes
- Consult with supervisor, and multi-disciplinary treatment team, to formulate case conceptualizations and treatment plans
- Administer/score/interpret psychological testing with clinical measures, when appropriate

Population: Primarily multi-ethnic adults awaiting adjudication; evaluations conducted in inpatient setting, using telepsychology technology when necessary
Supervisors: Elizabeth Bolinger, Ph.D.

December 2021-April 2022 — **Doctoral Intern, Juvenile Forensic Evaluation rotation**
Child Study and Treatment Center
Lakewood, WA

Responsibilities:
- Observe and co-lead court-ordered, pre-trial evaluations for justice-

involved youths under the direct supervision of a licensed forensic examiner
- Co-author reports describing evaluation, and providing diagnostic impressions and psycholegal opinions
- Consult with supervisor to formulate psycholegal opinions in accordance with state statutes
- Administer/score/interpret psychological testing with clinical and/or forensic measures, when appropriate

Population: Primarily multi-ethnic juveniles awaiting adjudication; evaluations conducted in inpatient and outpatient settings, using telepsychology technology when necessary

Supervisors: Fran Lexcen, Ph.D.

August 2021- December 2021
Doctoral Intern, Competency Evaluation rotation
Office of Mental Health Services/Western State Hospital
Lakewood, WA

Responsibilities:
- Conducted court-ordered, pre-trial evaluations under the direct supervision of a licensed forensic examiner
- Co-authored reports describing evaluation and providing diagnostic impressions, psycholegal opinions, and a Designated Crisis Responder referral opinion
- Consulted with supervisors to formulate psycholegal opinions in accordance with state statutes
- Administered/scored/interpreted psychological testing with clinical and/or forensic measures, when appropriate

Population: Primarily multi-ethnic adults involved in the justice system; evaluations were conducted in inpatient and outpatient settings

Supervisors: Megan Kopkin, Ph.D. & Samantha J. Peterson, Psy.D.

January 2020 – May 2021
Student Clinician and Co-Facilitator
Team Forensic Services
Sex Offender Treatment Program
Huntsville, TX

Responsibilities:
- Co-facilitated bi-monthly, court-ordered, manualized group treatment with a Licensed Sex Offender Treatment Provider

Population: Primarily lower-functioning, low-income, multi-ethnic, adult males on probation or parole for sexual offenses

Supervisors: Holly Miller, Ph.D., LSOTP & Jennifer Rone, M.A., LSOTP

August 2019- August 2021
Practicum Student Clinician
Harris County Juvenile Probation Department
Houston, Texas

Responsibilities:
- Conducted court-ordered psychodiagnostic evaluations of justice-involved youth

- Conducted comprehensive clinical interviews with parents and juveniles
- Administered/scored/interpreted measures of intellectual and achievement abilities, behavior, and personality, including the KBIT-2, WRAT-5, WISC, ARES, Jesness, BRIA, & PAI-A
- Co-authored integrated reports documenting clinical findings, diagnostic formulations, and recommendations to assist with placement and probation decisions

- Conducted Risk-Need-Responsivity evaluations for serious, habitual juveniles who have been referred to the QUEST program, an intensive comprehensive therapy program designed for habitual, juvenile offenders who have not responded to previous treatments
  - Administered/scored/interpreted measures of intellectual and achievement abilities behavior, and personality, as well as risk assessment (i.e., SAVRY)
  - Co-authored treatment informed reports from a Risk-Need-Responsivity perspective
  - Consulted with supervisors to formulate diagnostic opinions
- Attended and participated in group supervision, clinical case presentations and weekly didactics. Topics included:
  - Forensic case law
  - Rorschach administration and interpretation
  - Multicultural issues
  - Gang culture and history
  - Juvenile sexual offending

Population: Primarily low-income, multi-ethnic juveniles awaiting adjudication

Supervisors: Uche Chibueze, Ph.D., ABPP, Nicole Dorsey, Ph.D., & Alexandra Tellez, Ph.D.

September 2017-August 2021 **Student Forensic Evaluator**
Psychological Services Center
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Conducted court-ordered, pre-trial evaluations under the direct supervision of a board-certified forensic examiner including Competency to Stand Trial and Mental State at the Time of the Offense
- Co-authored reports describing evaluation, providing psycholegal opinions, and providing treatment recommendations
- Consulted with supervisors to formulate psycholegal opinions in accordance with state statutes

Population: Primarily multi-ethnic adults involved in the justice system in several rural counties; evaluations conducted in jails, in outpatient clinic and via telepsychology technology

Supervisors: Mary Alice Conroy, Ph.D., ABPP, Wendy Elliott, Ph.D., ABPP, & Darryl Johnson, Ph.D.

September 2019- **Student Clinician and Co-Facilitator**
June 2020 *Team Forensic Services*
Sex Offender Treatment Program
Conroe, TX

Responsibilities:
- Co-facilitated bi-monthly, manualized group treatment with a Licensed Sex Offender Treatment Provider
- Provided individual psychotherapy for group members whose needs extended beyond the group context

Population: Primarily low-income, multi-ethnic adult males on probation for sexual offenses

Supervisor: Holly Miller, Ph.D., LSOTP

June 2018- **Practicum Student Clinician**
August 2019 *Telebehavioral Care*
(Previously Telehealth Counseling Clinic)
Bryan, Texas

Responsibilities:
- Provided individual psychotherapy (including suicide risk assessment/management, treatment planning, CBT, ACT Schema therapy and DBT skills) via video-conferencing technology
- Authored intake and termination reports and formulated case conceptualizations and diagnoses
- Coordinated patient care with local mental health service providers
- Attended and participated in group supervision, clinical case presentations and weekly didactics

Population: Primarily low-income, multi-ethnic adults from rural communities seeking outpatient services

Supervisors: Norma Erosa, Ph.D. & Carly McCord, Ph.D.

September 2017- **Practicum Student Clinician-Individual Therapist & Evaluator**
May 2019 *Psychological Services Center*
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Conducted intake evaluations, treatment planning sessions, and delivered individual psychotherapy
  - Interventions included suicide risk assessment/management, treatment planning, CBT, ACT, DBT skills and interpersonal therapy
  - Authored intake, termination and update reports
- Conducted comprehensive psychodiagnostic and psychoeducational evaluations
  - Administered/scored/and interpreted measures of intellectual and achievement abilities, behavior and personality
  - Co-authored integrated reports, provided relevant recommendations
  - and provided feedback to clients and referral agencies
- Attended and participated in group supervision and clinical case

presentations
- Consulted with supervisors to formulate diagnostic opinions and treatment protocols

Population: Primarily low income, multi-ethnic adults seeing outpatient services, as well as undergraduate students seeking educational assessments for academic accommodations

Supervisors: Jaime Anderson, Ph.D., Wendy Elliott, Ph.D.., ABPP, & Craig Henderson, Ph.D.

September 2017-May 2019 **Practicum Student Clinician-Individual Evaluator**
Psychological Services Center
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Conducted court-ordered or probation-referred psychodiagnostics evaluations of justice-involved youth
  - Comprehensive clinical interviews with probation staff, parents and juveniles, administered/scored/interpreted measures of intellectual and achievement abilities, behavior and personality
  - Co-authored integrated reports documenting clinical findings, diagnostic formulations, and recommendations to assist with placement and probation decisions
- Consulted with supervisors to formulate diagnostic opinions

Population: Ethnically diverse, justice involved youth
Supervisor: Darryl Johnson, Ph.D..

February 2015-September 2015 **Practicum Student Clinician**
King's County Court House
New York, NY

Responsibilities:
- Observed pre-trial evaluations for adult defendants, primarily Competency to Stand and Mental State at the Time of the Offense evaluations
- Consulted with supervisors to formulate psycholegal opinions in accordance with state statutes

Population: Primarily multi-ethnic adults involved in the justice system
Supervisor: Alan Perry, Ph.D.

ADDITIONAL CLINCAL/PROFESSIONAL EXPERIENCE

September 2019-Present **Litigation Consultant**
Scientific Resources for the Law
University of Nebraska-Lincoln

Responsibilities:
- Provided research and support services to trial consultants in pre-trial planning stages via jury selection services, data analysis and other related research services
- Preparing an article for publication Research Reviews, a new, monthly column in the American Society of Trial Consultants Newsletter

Supervisor: Eve Brank, JD, Ph.D.

May 2020 **Invited Lecturer**
Sensitivity trainings
Conroe ISD Police Department
Conroe, TX

Responsibilities:
- Creating training curriculum (potentially 4 8-hour trainings) focused on topics such as implicit bias, in group/out-group bias, preventing compassion fatigue, attitudinal change and normative social influence

Supervisor: Darryl Johnson, Ph.D.

June 2019 & August 2020 **Invited Lecturer**
Mental Health Police Officer and Crisis Intervention Team trainings
Conroe ISD Police Department
Conroe, TX

Responsibilities:
- Created training curriculum focused on relevant diagnoses and crisis intervention techniques
- Updated the pre-existing, state-mandated Crisis Intervention Team curriculum
- Led presentations and facilitated discussions
- Participated in role-play exercises with officers illustrating how to effectively communicate with mentally ill individuals in the community

Supervisors: Wendy Elliot, Ph.D., ABPP, & Darryl Johnson, Ph.D.

January 2019- January 2020 **Student Editorial Board Member**
Law and Human Behavior

Responsibilities:
- Reviewed submissions to the Journal of Law and Human Behavior and provide constructive edits

Supervisor: Marcus Boccaccini, Ph.D.

June 2020- August 2020 **Student Member**
SHSU Psychological Services Center Telehealth Task Force
Psychological Services Center
Huntsville, TX

Responsibilities:
- Facilitated and supported the transition of our outpatient mental health clinic to tele-mental health services
- Troubleshot initial operations
- Wrote manual for new telepsychology operations

Supervisor: Darryl Johnson, Ph.D.

June 2018- August 2019 **Sam Houston State University Campus Representative**
APA Division 41- American Psychology-Law Society
Sam Houston State University

Huntsville, Texas

Responsibilities:
- Disseminated information to students and faculty from a professional organization
- Acted as liaison between doctoral program, professional organization, and other entities with psycholegal interests
- Coordinated and planned the Sam Houston State University Social at the Annual AP-LS convention

Supervisor: Ariel Breaux, M.A.

September 2014- September 2015 **Office Assistant**
Forensic Mental Health Counseling office
John Jay College of Criminal Justice
New York, NY

Responsibilities:
- Processed incoming and outcoming correspondence
- Answered, screened, and referred inquiries
- Organized student paperwork including applications and externship logs
- Managed scheduling
- Represented the program at a variety of department and admission event

Supervisor: James Wulach, Ph.D., J.D.

May 2014- May 2015 **Coordinator**
Master's Student Research Group
John Jay College of Criminal Justice
New York, NY

Responsibilities:
- Served as a mentor to fellow students within the Forensic Psychology Master's Program
- Organized applicable programming and informational sessions regarding topics relevant to forensic psychology, career opportunities and professional development
- Coordinated the annual Master's Student Research Conference
- Collaborated with members of faculty and administration in order to better serve the student body
- Represented the Forensic Psychology Master's program at a variety of department and admission events

Supervisors: Diana M. Falkenbach, Ph.D. & Gabrielle Salfati, Ph.D.

TEACHING EXPERIENCE

January 2021- May 2021 **Graduate Teaching Assistant**
Abnormal Psychology, virtual (PSYC 3331.09)
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Designed course syllabus and course material
- Presented lectures
- Designed and graded course assignments and exams
- Held weekly office hours

Supervisor: Jorge Varela, Ph.D.

August 2017- May 2018
Graduate Teaching Assistant
Introduction to Psychology, undergraduate
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Designed course syllabus and course material
- Led lectures and group activities
- Designed and graded course assignments and exams
- Created study materials
- Held weekly office hours

Supervisor: Christopher Wilson, Ph.D.

January 2015- May 2016
Graduate Teaching Assistant
Developmental Psychology, undergraduate
John Jay College of Criminal Justice
New York, NY

Responsibilities:
- Assisted in the grading of exams and essays
- Facilitated group activities and discussions

Supervisor: Roberta Blotner, Ph.D.

August 2015- December 2015
Graduate Teaching Assistant
Psychopathy Assessment, graduate
John Jay College of Criminal Justice
New York, NY

Responsibilities:
- Assisted in the grading of course assignments
- Provided individual feedback pertaining to course assignments
- Provided individual supervision on the scoring of various items of the PCL-R
- Led and commented on class discussions on various topic such as substance abuse in psychopathic populations and gender differences in the presentation of psychopathy
- Provided assistance to students via email on course content and layout

Supervisor: Diana M. Falkenbach, Ph.D.

SUPERVISORY EXPERIENCE

September 2021- December 2021
Peer Supervisor
Office of Mental Health Services/Western State Hospital, Doctoral Internship
Lakewood, WA

Responsibilities:
- Facilitated supervision sessions of fourth-year doctoral student, focused on report writing, case conceptualization, general forensic topics, and professional development
- Provided supervision on clinical and forensic testing measures, when appropriate

Supervisor: Kayla L, Carson, Psy.D.

August 2019- May 2020 **Clinical Teaching Assistant**
Assessment of Intelligence and Achievement (PSYC 5395)
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Instructed students regarding standardized administration of various intelligence and achievement measures
- Supervised administration and scoring of numerous intelligence, achievement, and adaptive behavior measures to ensure student competence
- Provided personalized feedback on recorded administrations of intelligence and achievement measures
- Assisted in changes that facilitated the course to an online format following in person school closures during the COVID-19 pandemic
  - Recorded intelligence and achievement administrations with errors to be scored for accuracy
  - Scored protocols for accuracy
  - Provided feedback to students
  - Compiled electronic resources for students

Supervisor: Ramona Noland, Ph.D.

June 2018- August 2018 **Peer Supervisor**
Introduction to Doctoral Practicum Course (PSYC 8382)
Department of Psychology & Philosophy
Sam Houston State University
Huntsville, Texas

Responsibilities:
- Co-facilitated supervision sessions of first-year doctoral students with clinic director
- Reviewed taped mock therapy sessions and provided feedback on therapeutic techniques
- Served as a mock therapy client for students practicing suicide risk assessments, as well as general therapeutic techniques

Supervisor: Mary Alice Conroy, Ph.D., ABPP

PEER-REVIEWED PUBLICATIONS

Long, T. A., **Reinhard, E.**, Sellbom, M., & Anderson, J. L. (2020). An Examination of the Reliability and Validity of the Comprehensive Assessment of Traits Relevant to Personality Disorder–Static Form (CAT-PD-SF). *Assessment*, Advanced online publication. doi: 10.1177/1073191120907957

Iturri, F., Gale-Bentz, E., **Reinhard, E. E.**, Hunter, T. B., McCann, C. N., Zaman, A., ... & Tellez, A. (2020). Incarceration and pandemic-related restrictions during COVID-19: An empathic understanding of two worlds. *Psychological Trauma: Theory, Research, Practice, and Policy, 12*(S1), S233-S235.

Reinhard, E.E., Trupp, G., Ricardo, M., & Johnson, D. (2020). Competent to work from home?: Forensic evaluations in the midst of a global pandemic. *Texas Psychologist, 79*(2), 8-10.

Falkenbach, D. M., **Reinhard, E. E.**, & Zappala, M. (2019). Identifying psychopathy subtyping using a broader model of personality: an investigation of the Five Factor Model using model-based cluster analysis. *Journal of Interpersonal Violence, 85*, 117–122.

Falkenbach, D. M., Beltrani, A., & **Reinhard, E. E.** (2018). Deriving Psychopathy Subtypes using Model-Based Cluster Analysis. *Sage Research Methods*. Online. *1-16*.

Falkenbach, D. M., **Reinhard, E. E.**, & Larson, F. R. (2017). Theory based gender differences in psychopathy subtypes. *Personality and Individual Differences*, *105*, 1-6.

Falkenbach, D. M., Barese, T. H., Balash, J., **Reinhard, E. E.**, & Hughs, C. J. (2015). The exploration of subclinical psychopathic subtypes and their relationship with types of aggression in female college students. *Personality and Individual Differences*, *85*, 117-122.

MANUSCRIPTS IN PROGRESS

Hart, J. R., **Reinhard, E. E.,** Boccaccini, M. T., Domino, M., & Cooper, V. (In Preparation). Correspondence Between Structured Interview of Reported Symptoms' (SIRS) Scores and Clinicians' Opinions of Malingering.

Reinhard, E.E., Schiafo, M., & Anderson, J. L. (In Preparation). Understanding Linguistic Correlates of Sexual Aggression in College-Aged Males.

CONFERENCE PAPER AND POSTER PRESENTATIONS

Reinhard, E., Schiafo, M., & Anderson, J. L. (2020, March). *Understanding Linguistic Correlates of Sexual Aggression in College-Aged Males.* Paper presented at the 2020 American Psychology-Law Society conference, New Orleans, LA.

Bryson, C. N., Boccaccini, M. T., Gowensmith, W. N., **Reinhard, E**., & Holdren, S. (2019, March). *Does time matter in competency to stand trial evaluations?* Paper presented at the annual convention of the American Psychology-Law Society, Portland, OR.

Hart, J. R., **Reinhard, E. E.,** Boccaccini, M. T., Domino, M., & Cooper, V. (2018, March). *Correspondence Between Structured Interview of Reported Symptoms' (SIRS) Scores and Clinicians' Opinions of Malingering.* Paper presented at the American Psychology-Law Society conference. Memphis, TN.

Bryson, C. N., Boccaccini, M. T., Gowensmith, W. N., Laxton, K. L., Mattos, L., **Reinhard, E.**, Holdren, S., & Lawrence, J. (2018, March). *Time Matters in Competency to Stand Trial Evaluations.* Poster presented at the American Psychology-Law Society, Memphis, TN.

Laxton, K. L., Varela, J. G., Bryson, C. N., Mattos, L. A., **Reinhard, E. E.**, Holdren, S. M., Lawrence, J., & Minor, B. R. (2018, March). *Content and Quality of Forensic Evaluation Reports of Competency to Stand Trial Evaluations.* Poster presented at the American Psychology-Law Society, Memphis, TN.

Long, T., **Reinhard, E. E.**, Anderson, J. L., & Sellbom, M. (2018, March). *An examination of the reliability and validity of the Computerized Adaptive Test of Personality Disorder- Static Form (CAT-PD-SF).* Poster presented at the Society for Personality Assessment Conference, Washington, D.C.

Grose-Fifer, J., Larson, F., Aveson, O., **Reinhard, E.** & Bonfiglio, E. (2017, October). *Empathic concern and emotional sentence processing: An N400 study*. Poster presented at the Society for Psychophysiological Research conference, Vienna, Austria.

Camins, J. S., Henderson, C. E., Magyar, M. S., Schmidt, A. T., Crosby, J., **Reinhard, E. E.**, & Boland, J. K., (2017, March). *Adolescent behavior typing in at-risk youth: Validation using a latent variable approach*. Paper presented at the annual American Psychology-Law Society Conference, Seattle, WA.

Falkenbach, D. M., Zappala, M., & **Reinhard, E. E.** (2016, March). *Identifying psychopathy subtypes using a broader model of personality: An investigation of the Five-Factor Model using model-based cluster analysis.* Paper presented at the American Psychology-Law Society conference. Atlanta, GA. Kirilko, E., Medina, A., **Reinhard, E.**, Bonfiglio, E., & Grose-Fifer, J. (2015, June). *Anticipation to emotional stimuli and psychopathy: An ERP study.* Poster presented at the Cognitive Neuroscience Society meeting. San Francisco, CA.

Kirilko, E., Medina, A., **Reinhard, E.**, Bonfiglio, E. & Grose-Fifer, J. (2015, March). *Differential expectatory neural responses to emotional stimuli in psychopathic and nonpsychopathic undergraduates.* Poster presented at the Eastern Psychological Association conference, Philadelphia, PA.

Reinhard, E., & Falkenbach, D. (2013, May). *Psychopathy, Empathy, and Helping Behavior.* Paper presented at the Master's Student Research 2015 Conference. New York, NY.

RESEARCH EXPERIENCE

August 2021- **July 2022**	**Doctoral Intern, Program Evaluation** *Washington State Department of Social and Health Services (DSHS)* Lakewood, WA

Supervisors: Rheanna Remmel, Ph.D. and James Vess, Ph.D.
Project: Program Evaluation of Breaking Barriers Competency Restoration Program in the state of Washington

- Evaluate fidelity of implementation of Breaking Barriers program and outcomes
- Over the course of the doctoral internship year, the following research tasks will be completed:
- Evaluate fidelity of implementation of Breaking Barriers program and outcomes
- Organize data and analyze results
- Write report and present findings to stakeholders

August 2016-Present **Graduate Research Assistant**
Sam Houston State University
Huntsville, Texas
Supervisor: Marc Boccaccini, Ph.D.

- Assisted in project preparation, specifically my dissertation investigating response style subtypes in a sample of male Sexually Violent Predator (SVP) evaluees
- Aided in data coding of forensic reports from the outpatient Psychological Services Clinic
- Aided in data analysis
- Assisted in developing national conference presentations
- Co-authored manuscripts

August 2016-Present **Graduate Research Assistant**
Sam Houston State University
Huntsville, Texas
Supervisor: Jaime Anderson, Ph.D.

- Assisted in project preparation
- Aided in data analysis, utilizing self-report measures, factor analysis and language analysis software
- Assisted in developing national conference presentations
- Co-authored manuscripts

August 2014-August 2016 **Graduate Research Assistant**
John Jay College of Criminal Justice
New York, NY
Supervisor: Jill Grose-fifer, Ph.D.

- Assisted in data collection utilizing an electroencephalogram (EEG)
- Assisted in developing national and international conference presentations

August 2013-August 2016 **Graduate Research Assistant**
John Jay College of Criminal Justice

New York, NY

Supervisor: Diana M. Falkenbach, Ph.D.

- Assisted in project preparation, specifically my thesis project analyzing empathy and helping behavior in an undergraduate population
- Aided in data collection with the New York Police Department
- Aided in data coding for various projects, with undergraduate samples and police officer samples
- Assisted in developing national conference presentations
- Co-authored manuscripts

August 2013-May 2014 **Graduate Research Assistant**

John Jay College of Criminal Justice

New York, NY

Supervisor: Steven D. Penrod, Ph.D.

- Aided in data collection and coding of periodicals pertaining to pretrial publicity

August 2011-May 2012 **Undergraduate Research Assistant**

Drew University

Madison, NJ

Supervisor: Graham Cousens, Ph.D.

- Aided in data collection with animal subjects, investigating the effect of nicotine use on decision making

SERVICE & LEADERSHIP POSITIONS

Graduate Student Mentor to a First-Year Doctoral Student (2020-2021)

Volunteer Assistant Event Coordinator, American Academy of Forensic Psychology Contemporary Issues in Forensic Psychology Continuing Education (Virtual) Workshops (September 2020)

Volunteer Assistant Event Coordinator, American Academy of Forensic Psychology Contemporary Issues in Forensic Psychology Continuing Education Workshops (April 2019)

Conference Presentation Student Reviewer, American Psychology and Law Society (2018-2019)

AWARDS & SCHOLARSHIPS

2016-2020 Student Travel Award ($1000)

Sam Houston State University

2008-2012 Merit Based Scholarship

Drew University