2024

Identifying mechanistic pathways to rigidity associated with Obsessive-Compulsive Personality Disorder traits using a novel decision-making paradigm

Hannah L. Heintz
Virginia Commonwealth University

Identifying mechanistic pathways to rigidity associated with Obsessive-Compulsive Personality Disorder traits using a novel decision-making paradigm

by

Hannah Heintz
Bachelor of Arts, University of Vermont, 2015

A thesis submitted in partial fulfillment for the requirements of the degree of Master of Science in Clinical Psychology at Virginia Commonwealth University.

Chair: Ann F. Haynos, Ph.D,
Assistant Professor, Department of Psychology

Committee Members:
Kelsey Hagan, Ph.D.
Jared Keeley, Ph.D.

Virginia Commonwealth University
Richmond, Virginia
April 25, 2024

Table of Contents

List of Tables

List of Figures

Abstract

IDENTIFYING PATHWAYS TO RIGIDITY ASSOCIATED WITH OBSESSIVE COMPULSIVE PERSONALITY DISORDER TRAITS USING A NOVEL DECISION-MAKING PARADIGM

By Hannah L. Heintz, B.A.

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University.

Virginia Commonwealth University, 2024.

Chair: Ann F. Haynos, Ph.D.

Cognitive and behavioral rigidity is observed across several mental disorders and is a defining characteristic of Obsessive-Compulsive Personality Disorder (OCPD), a highly prevalent and debilitating, yet understudied, disorder. In particular, treatments for OCPD are underdeveloped due to our poor understanding of the mechanisms leading to the disorder's key feature of rigidity. Two related disorders, anorexia nervosa (AN) and obsessive-compulsive disorder (OCD), have shown distinct mechanistic pathways leading to symptoms of rigidity, indicating that this trait can arise as a result of a number of differentially impaired cognitive processes, each requiring unique interventions. To examine the relationship between symptoms of OCPD and abnormalities in the decision-making processes which may manifest in rigidity, participants (n=83) completed the Web-Surf task, a novel decision-making paradigm, in addition to the Five-Factor Obsessive-Compulsive Inventory (FFOCI-SF), a self-reported continuous measure of OCPD traits. Results indicated that, similar to the pattern observed in AN, OCPD traits predicted heightened selectivity relative to reward (p = .009). In addition, OCPD traits predicted accelerated behavioral adaptation following experiences of cost or reward (p < .001), which deviated from patterns expected in AN and OCD. An exploratory analysis revealed decreased selectivity relative to cost among individuals with the highest OCPD traits (p = .016).

Results further indicated that specific OCPD trait domains, particularly conscientiousness, may be influenced by distinct aberrations in these decision-making processes. Our findings provide valuable insight into shared mechanisms between OCPD and AN as well as the distinction between OCPD and OCD. Implications for treatments and directions for future research are discussed.

Identifying mechanistic pathways to rigidity in Obsessive-Compulsive Personality Disorder using a novel decision-making paradigm

Obsessive-compulsive personality disorder (OCPD) is a psychological condition marked by cognitive and behavioral rigidity, including extreme preoccupation with detail, stern perfectionism, excessive perseveration, fixation with rule-following, and restricted affect (American Psychiatric Association, 2022). In the International Classification of Diseases (ICD-11) dimensional model, the same disorder is diagnosed using the Anankastia trait domain specifier for a general Personality Disorder (Gecaite-Stonciene et al., 2021; World Health Organization, 2019). OCPD and its traits co-occur with a number of other disorders - most frequently, eating disorders and obsessive-compulsive disorder (OCD) (Starcevic & Brakoulias, 2014). Individuals with OCPD engage in otherwise adaptive behaviors in a manner that is inflexible and extreme, at the expense of achieving goals and maintaining relationships. For example, an individual with OCPD may impose impossibly high standards on themself such that a project can never be completed, leading to guilt and shame, or follow rules so literally that a slight discretion might be regarded as a moral failing (American Psychiatric Association, 2022). These symptoms are associated with poor outcomes, including reduced quality of life, marked impairment in psychosocial functioning, and heightened suicidality (de Reus & Emmelkamp, 2012; Diedrich & Voderholzer, 2015). Further, OCPD presents a high economic burden and is associated with the highest direct medical costs and productivity losses among all personality disorders (PDs), except Borderline PD, which demonstrates similar impairment (Soeteman et al., 2008). Affecting approximately 6.5% of the population globally, OCPD is ranked among the most prevalent personality disorders (Clemente et al., 2022). Despite its enduring inclusion in psychological nosology, high prevalence in the general population, and significant cost to society, the etiology and pathophysiology of the disorder remain significantly understudied and, therefore, poorly understood.

Shifting Toward a Dimensional Model of Personality

OCPD has been included in the Diagnostic and Statistical Manual for Mental Disorders (DSM) since its first edition as a Cluster C personality disorder. However, long-standing discussions regarding the numerous shortcomings in the diagnostic criteria for PDs have signaled the necessity for a major shift away from reliance on categorical approaches alone. These issues include overlapping criteria between PDs and insufficient clinical relevance of PD categories resulting in a high prevalence of "PD Not Otherwise Specified" diagnoses (Verheul & Widiger, 2004), and reliance on polythetic criterion sets (i.e., only needing to meet a certain number of, but not all, listed criteria) with a lack of defining "core symptoms" leading to considerable heterogeneity in clinical presentation among those diagnosed (Starcevic & Brakoulias, 2014; Widiger & Trull, 2007). Integrating findings from OCPD research using these inconsistent and imprecise categorical diagnostic criteria is difficult at best, and thus, conclusions about its true nature and relationships with other disorders to date are inadequate.

To address these concerns, new dimensional classification systems for PDs have emerged. Rather than attempting to partition personality dysfunction into distinct diagnostic categories, the Alternative DSM-5 Model for Personality Disorders (AMPD) is a hybrid dimensional-categorical approach that focuses on indicating the severity of disturbances in self and interpersonal functioning (ranging from normal/adaptive to extreme) and profiling specific maladaptive trait domains (American Psychiatric Association, 2022). The AMPD maladaptive trait domains are explicitly based on the Five-Factor Model of personality, an empirically-supported model that conceptualizes personality along dimensions of five core traits (McCrae &

John, 1992): Detachment (versus Extraversion), Antagonism (versus Agreeableness), Disinhibition (versus Conscientiousness), Negative Affectivity (or Neuroticism) and Psychoticism (an extreme of Openness to Experience) (Suzuki et al., 2017). These domains are further divided into lower-order facets for more specificity in assessment (Costa & McCrae, 1995). OCPD as a specific diagnosis is retained in the AMPD but is now defined by the required "core symptom" of rigid perfectionism, alongside additional maladaptive traits of intimacy avoidance, perseveration, and/or restricted affectivity.

From the perspective of the Five-Factor Model, prototypic OCPD falls at the high extreme of conscientiousness (specific trait facets include competence, order, dutifulness, achievement-striving, deliberation, self-discipline), while also displaying low openness (to feelings, actions, and values), low extraversion (specifically, low warmth and excitement-seeking), and high neuroticism (negative affectivity) (Samuel et al., 2012). Several lines of evidence support the idea that personalities falling at the most extreme poles of these trait dimensions will experience distress and impairment. While adaptive at normal levels, extreme conscientiousness—specifically, the facets of competence, self-discipline, and dutifulness—is associated with lower wellbeing and negative affect (Carter et al., 2016). Low openness underlies difficulty adapting to change, inability to tolerate diverse viewpoints, and constricted emotions (Piedmont et al., 2009). Further, elevated risk of suicidality and non-suicidal self-injury may be of concern in individuals with low extraversion and high neuroticism (Arthurs & Tan, 2017; Fang et al., 2012). This illustrates how different personality dimensions associated with OCPD may be responsible for different sets of negative outcomes resulting from this disorder. Thus, research that employs dimensional measurement of maladaptive personality traits consistent with OCPD stands to present a clearer, more accurate conceptualization of this disorder. Additionally, homing in on the relations between specific OCPD traits and mechanisms underlying the key feature of rigidity in this disorder will improve understanding of its etiology, and inform targeted interventions.

Lack of Treatments for OCPD Necessitates More Precise Mechanistic Models

Despite the high prevalence and severity of OCPD and its associated traits, our primitive understanding of the fundamental mechanisms of this disorder have hindered high-quality and large-scale research on effective treatments. The lack of a unitary etiological model for OCPD can be at least partly traced back to the deficiencies of the DSM's categorical diagnostic system, which encompass multiple distinct subtypes of the disorder, each linked to different clinical and biological correlates (Fossati et al., 2006; Riddle et al., 2016). As a result, treatment literature has remained virtually inert, generating limited formal clinical guidelines, much less a gold-standard treatment. While a few treatment modalities show promise, the overall quality of the research is limited, and no comparative studies have been conducted.

A small number of non-controlled studies have shown a reduction in PD symptom severity, depression, and anxiety for individuals with an OCPD diagnosis following courses of Cognitive or Cognitive-Behavioral Therapy (Cummings et al., 2012; Enero et al., 2013; Ng, 2005; Strauss et al., 2006). Two case studies with OCPD have shown improvement in interpersonal functioning following Metacognitive Interpersonal Therapy (Cheli et al., 2020; Dimaggio et al., 2011). A recent controlled trial of this intervention demonstrated efficacy in reducing interpersonal problems and emotion processing in a mixed-PD sample; however, the number of participants with OCPD was not reported (Popolo et al., 2022). Thus far, no controlled trials of Metacognitive Interpersonal Therapy specific to OCPD have been conducted. A newer intervention targeted for "disorders of overcontrol" (Lynch et al., 2015), Radically Open

Dialectical Behavior Therapy (RO-DBT), seems poised to reduce the problematic rigidity associated with OCPD, but the evidence for its efficacy in OCPD is limited to a single case study in a patient with comorbid paranoid PD (Lynch & Cheavens, 2008). Overall, these studies are limited by small or singular sample sizes, a lack of control groups, participants with co-occurring PDs, and a reliance on categorical diagnosis, which is likely to have resulted in a highly heterogenous sample. While affective symptoms and interpersonal functioning may be appropriate targets for acute improvement, there is no evidence that these treatments impact the overarching rigidity that characterizes OCPD.

Instead of continuing to approximate the best course of treatment for this condition based on underdeveloped etiological models, future research will benefit from improved clarity regarding the mechanisms of OCPD in order to determine how and why certain therapies may be beneficial, and for whom (Kramer et al., 2022). Additionally, scant attention has been paid to the role of individual AMPD trait domains or facets in predicting treatment response, an approach widely advocated for by experts (Kramer et al., 2022; Pinto et al., 2022). Given the recent transition toward dimensional, trait-specified diagnostic approaches, it is imperative for mechanistic research to examine the influence of individual maladaptive personality traits on core pathways to dysfunction in OCPD. Thus, refinement of the etiological model of OCPD through uncovering mechanistic pathways underlying its central features will set the stage for more precise and comprehensive intervention research.

Rigidity as a Target for Additional Research

Cognitive and behavioral rigidity may be the “missing mechanistic link” to developing effective interventions that target the core pathology of the disorder. Frequently endorsed and highly stable (McGlashan et al., 2005), rigidity is the root cause of impairment in interpersonal functioning in OCPD, leading to distress (Cain et al., 2015; Villemarette-Pittman et al., 2004). Rigidity is also associated with poorer treatment outcomes. During the psychotherapeutic process, cognitive and emotional rigidity may impede the establishment of rapport between client and therapist, and the ability to engage in key aspects of cognitive and behavioral therapies (e.g., challenging dysfunctional thoughts, shifting behavioral patterns) (Pinto et al., 2022). Nonetheless, current interventions fall short of adequately addressing this harmful trait. As emotional dysregulation and behavioral impulsivity is thought to underlie much of psychopathology, many psychotherapeutic treatments, including cognitive and behavioral therapies, are targeted toward enhancing self-control and executive functioning (e.g., Anderson et al., 2021; Sloan et al., 2017). The impairments seen in OCPD instead reflect rigidity that may arise from maladaptive *over*-regulation of thoughts, behaviors, and emotions. Therefore, most standard treatments may not be effective for OCPD as they may actually serve to enhance aspects of rigidity, such as behavioral inhibition and excessive delay of gratification. The few treatments designed to reduce rigidity, such as Cognitive Remediation Therapy and RO-DBT, are still in their infancy (Gilbert et al., 2020; Hagan et al., 2020); therefore, conclusions regarding their efficacy in OCPD and other disorders are currently limited. Without an improved understanding of the mental processes that lead to the unexplained rigidity in OCPD, interventions are likely to remain insufficient.

Understanding Rigidity in OCPD Through Similarities with Other Disorders

In addition to being a key feature of OCPD, cognitive and behavioral rigidity is observed across many psychiatric diagnoses, including major depressive disorder, generalized anxiety disorder, autism, OCD, and eating disorders such as anorexia nervosa (AN) (Uddin, 2021). Appreciable evidence has accumulated to show that rigidity predicts greater symptom severity and/or poorer response to psychotherapeutic treatment in these disorders (Jennings, 2023; Quilty et al., 2013; Smith et al., 2017; Stotts et al., 2015; Zvolensky et al., 2014). Scholars have debated regarding the nature of the association between of OCPD, OCD, and AN, disorders that share symptoms of rigidity, such as following strict routines, perfectionism, and inflexibility (Young et al., 2013). Some evidence exists supporting an etiological relationship between the three, such as the finding that OCPD traits are a familial risk factor for both AN (Strober et al., 2007) and OCD (Calvo et al., 2009). In fact, AN has even been posited as a "modern obsessive-compulsive syndrome" (Rothenberg, 1986). Despite these commonalities, research remains inconclusive regarding the degree to which there is a mechanistic overlap between the disorders. Several studies have found appreciable differences when comparing OCD, OCPD, and AN on a number of indices, including decision making under uncertainty (Luo et al., 2020), planning ability (Paast et al., 2016), capacity to delay reward (Pinto et al., 2014; Steinglass et al., 2017) and set-shifting (Bohon et al., 2020). Similar to the way in which a medical symptom like shortness of breath can result from multiple causes, each requiring distinct interventions, inflexible behavior may be caused by a number of different cognitive processes (Ionescu, 2012; Serpell et al., 2002; Treadway & Zald, 2013). While rigidity appears to be a strong throughline multiple psychiatric disorders, it may arise from differentially impaired decision-making in each disorder – therefore, effective, targeted treatment relies on identifying the specific variations in these processes that lead to the expression of this trait.

Neuroeconomics in the Study of Psychopathology

One approach to more precisely defining the cognitive processes contributing to rigidity in OCPD is to adopt the novel theoretical and analytical methods arising from the field of neuroeconomics. Neuroeconomics integrates literature from fields such as economics, neuroscience, and psychology. Using this integrative approach, neuroeconomic theories postulate that a series of specific mental calculations, or computations, underlie effective decision-making and that understanding miscalculations in these processes can provide clues for understanding the biobehavioral mechanisms maintaining psychological disorders. These calculations can include those evaluating the balance of cost versus reward, assessing the time and effort needed to access a potential reward, predicting outcomes based on context and previous experiences, and considering preferences when making choices (Engel & Cáceda, 2015). Notably, alterations in each of these computations and others could yield behavioral rigidity, as a given behavior can be explained by a number of underlying processes (Redish et al., 2021). For instance, excessive focus on prioritizing reward over cost could lead to narrow and rigid pursuit of certain pleasurable experiences, as is seen in chronic drug use or binge eating (Koob & Volkow, 2016). On the other hand, over-estimating the costs of effort could lead to the rigid focus on low-effort activities, as is seen in the case of depression (Treadway & Salamone, 2022). Although both situations would manifest as cognitive and behavioral rigidity, these different computational disturbances would require different types of interventions.

Neuroeconomic tasks can help to operationalize and measure these different computations by asking subjects to make economic choices under specific circumstances, thus allowing researchers to examine how and when individuals with mental illnesses deviate from "optimal" decision-making (Glimcher & Rustichini, 2004; Robson et al., 2020). Chronic lapses during this process, such as under-estimation of costs or inappropriate use of a decision strategy, can result in behaviors that ultimately lead to harmful consequences; therefore, neuroeconomic tasks are important tools in the investigation of numerous processes thought to be disrupted across psychiatric disorders (Addicott et al., 2017). A growing literature has employed neuroeconomic methods to support or develop theories of impaired decision-making in addictions (to both substances and behaviors, such as gambling) (Engel & Cáceda, 2015; Redish et al., 2008), eating disorders (Guillaume et al., 2015; Haynos, Abram, et al., 2020), and Borderline PD (Paret et al., 2017). These emerging findings have potential to lead to significant advances in treatments by identifying mechanisms in a more precise, and therefore accurate, manner (Haynos et al., 2022). By closely examining the decision-making processes in OCPD via neuroeconomic tasks, we can better characterize the unexplained rigidity seen in this disorder in comparison to extant knowledge of other disorders.

Using Foraging Models to Link Animal and Human Decision-Making

One set of neuroeconomic tasks that can provide novel insights into the decision processes leading to rigidity are those developed from foraging models. Stemming from evolutionary accounts of behavior, foraging models provide a framework for behavior across a sequence of choices when important resources are scarce and potential alternatives are available (Stephens, 2008). In animals, foraging occurs when gathering food; in humans, foraging for food is rare—however, foraging models can be applied to understand multi-option scenarios in which valuable resources (e.g., time, money, energy) are limited and immediate choices can impact future options, such as searching for and deciding to accept a new job or buy a house. While foraging, both species face a series of choices between exploiting a known reward and relinquishing unknown alternatives, or abandoning the current reward and exploring other options, in order to maximize these resources. We can estimate the relative value of each choice depending on a complex interplay of factors, such as the organism's preference for different options, the time or effort required to explore, the probability of greater rewards elsewhere, the advantages of prioritizing short- versus long-term goals. With knowledge of these factors, researchers can model what optimal decision-making would consist of based on the relative cost and benefit of each choice (Stephens, 2008). Neuroeconomic tasks that replicate foraging scenarios in a controlled, testable setting allow researchers to more thoroughly understand this complicated process and construct a normative framework of decision-making in both humans and non-human animals (Glimcher & Rustichini, 2004; Kalenscher & van Wingerden, 2011).

By employing neuroeconomic foraging tasks that are functionally comparable between animals and humans, we can achieve a level of precision about the neural mechanisms underlying certain decision-making behaviors while maintaining a link to ecological validity. One recently developed translational foraging paradigm is the rodent Restaurant Row task (Steiner & Redish, 2014) and the corresponding human Web-Surf task (Abram et al., 2016). These are foraging tasks designed examine parallel decision processes across species. Restaurant Row requires a rodent to travel through a loop-shaped maze with four protruding arms (“restaurants”), each of which produce a differently-flavored food pellet. Food pellets can be accessed from each restaurant after a randomly assigned delay, which is signaled to the rodents through the pitch of an auditory tone. Web-Surf parallels this design by immersing human participants in a time-limited “web-surfing” environment during which participants virtually navigate through four galleries presenting pleasant video clips (see **Figure 1**). In the Web-Surf task, the random time day is signaled through a visual download bar, rather than an auditory tone. When navigating Restaurant Row or the Web-Surf task, an organism enters a restaurant or gallery, at which point they are alerted to the random delay assigned to that trial (between 1-30 seconds). The tasks are time-limited, meaning decisions to stay and wait for the current reward (i.e., food pellet, video) or skip and travel to the next option should be balanced appropriately in order to maximize the reward obtained during the session. Decisions within these paradigms are affected by numerous variables, including the length of the delay offered, category (flavor/genre) preferences, and the outcome of previous trials.

Analysis of behavior during the Restaurant Row and Web-Surf tasks has yielded pioneering insights into choice behaviors and their underlying neural mechanisms across species. For example, both rodents and humans display evidence of preferences for certain reward categories over others, signaled by their willingness to wait longer, on average, for offers within particular categories compared to others (Abram et al., 2016). Humans also rate more preferred videos as more enjoyable (Abram et al., 2016) and rodents spend longer lingering in more preferred restaurants even after the reward is delivered (Sweis, Thomas, et al., 2018). Decisions to stay or skip occur quickly and efficiently when an offer is clearly high- or low-value (i.e., the delay is significantly shorter or significantly longer than the length of time one is willing to wait, or their "decision threshold") (Abram et al., 2019; Steiner & Redish, 2014). However, decisions take longer and are more computationally demanding as the offer nears one's threshold and choices become more ambiguous. Overall, however, both rodents and humans move more quickly as they progress through the task (Huynh et al., 2021; Sweis, Thomas, et al., 2018).

Comparison of rodent neurophysiology, human neuroimaging, and physical behaviors during these tasks has further revealed that across species, nearly identical processes occur during difficult decisions. Physical "pause and look" behavior accompanying activation in the medial prefrontal cortex and hippocampus indicates a mental evaluation of possible outcomes associated with each choice based on knowledge of previous results and prospection of future outcomes (Abram et al., 2019; Huynh et al., 2021; Redish, 2016; Schmidt et al., 2019). Both rodents and humans also show susceptibility to the "sunk cost" fallacy, or the tendency to base a decision on the amount of time and effort that has already been spent, regardless of the fact that the chosen action ultimately incurs more costs than benefits. During Restaurant Row and Web-Surf, one may choose to "quit" in the wait zone (i.e., after choosing to accept an offer, but prior to receiving the reward), therefore abandoning the reward despite already having invested time. Cross-species parallels show a decreased willingness to "quit" as time spent in the wait zone increases, indicating that the more time already spent waiting for a reward, the more one's willingness to invest additional time increases (Sweis, Abram, et al., 2018). Taken together, the existing literature on these paradigms in healthy samples highlights dissociable elements of the decision-making process that can alter choice behavior on this task.

The unique ability of these tasks to quantify both behavioral and neural aspects of the decision-making process positions them as highly useful methodologies in the study of psychopathology. For example, sub-optimal foraging patterns have been observed in frequent gamblers and individuals with ADHD, who tend to over-rely on exploration at the expense of valuable outcomes, potentially signifying a propensity towards reward-seeking behaviors even when these behaviors result in losses (Addicott et al., 2015; Van den Driessche et al., 2019). Further, both positive and negative symptom dimensions in schizophrenia are linked to over-reliance on random versus directed exploration and maladaptive switching between exploration and exploitation during foraging (Speers & Bilkey, 2023). Using the Web-Surf task, we can observe multiple specific facets of complex decision-making processes: in this project, we will specifically focus on identifying abnormalities in aspects of decision-making that may lead to behavioral rigidity in OCPD, including choice decisiveness, choice selectivity, and behavioral adaptation.

Decisiveness. When choosing between options, decisiveness refers to the ability to commit to a particular choice efficiently and with certainty—in contrast with indecisiveness, which is slower and involves mentally gathering and considering evidence for each option. We can assume that individuals are motivated to obtain a desired outcome and avoid undesired outcomes (Gold & Shadlen, 2007). Given the limited time economy in the Web-Surf task, participants want to watch highly valued videos and to avoid wasting time making decisions or accepting offers with long delays. Evidence to date supports this idea, as both rodents and humans exhibit more uncertainty (i.e., slower reaction times) early in the task as they begin to gather useful information (Huynh et al., 2021; Sweis, Thomas, et al., 2018) and for more difficult decisions closer to their decision threshold (Abram et al., 2019; Steiner & Redish, 2014). An optimal decision-making strategy should seek to balance contemplation and efficiency across the task in order to maximize time spent watching preferred videos and reduce time spent waiting and watching less preferred videos; therefore, patterns which show an imbalance may indicate impairment. We can quantify decisiveness on the Web-Surf task through examining how time is spent across the task – in particular, speed at moving through different portions of the trials. Indecisiveness would manifest in greater portions of the task being spent making decisions, rather than in other aspects of the task (e.g., navigating between decisions) and completing fewer trials (i.e., less opportunity for reward) due to this slower choice selection time. In this case, both over- and under- decisiveness may reflect rigid behavior. Over-decisiveness may lead to prematurely limiting reward options without sufficient consideration and under-decisiveness may lead to perseverating on making the “right” choice, thereby reducing time dedicated to future choices.

Selectivity. Choice selectivity is another metric through which we can examine rigidity. This parameter is highly related to decisiveness in that it focuses on willingness to sample various options across trials. However, whereas decisiveness references the speed at which decisions are made, selectivity references the types of choices being made. When faced with a sequence of choices over time, individuals may choose to sample a wide range of options, including less preferred and lower-value options, or to pursue only the most preferred and highest-value options. Ideally, decisions should seek to maintain a balance between the two courses of action in order to maximize cumulative rewards and minimize cumulative costs. An example of this is ordering takeout after moving to a new city—at first, exploration is helpful, and a person might sample a wide range of different restaurants. Over time, however, they become more selective as they learn which places are their most preferred, and begin to reliably order from only those. Moving towards selectivity too quickly (e.g., only ordering from the first restaurant tried) or continually over-sampling (e.g., perpetually trying new restaurants) may both reflect dysfunction in a number of decisional processes, including over-estimation of the costs of exploring and decreased reward learning (Addicott et al., 2017). Through examination of the proportion of stay versus skip decisions on offers, and how these relate to video preferences and time delays, we can characterize the patterns in choice selectivity that contribute to rigidity.

Behavioral Adaptation. When foraging, it is advantageous to continue to make choices that have resulted in reward and to avoid choices that have proven costly in order to ensure survival; thus, it is expected that an individual will adapt their behavior over time in response to gathering additional information about the outcomes associated with particular choices (Verharen et al., 2020). During a sequential decision-making task, an initial "learning" period is to be expected during which participants may be more willing to repeat unsuccessful actions (e.g., will continue to choose a video category that they have not enjoyed in the previous trial) until they become more confident in their own preferences (Abram et al., 2016). At a certain point, the participant should begin to adjust their stay-skip decisions based on the information that they have received in the prior trial (e.g., how much they liked that category of video)—a higher rating should predict a greater likelihood of staying for that same category in the future, while a lower rating should predict a greater likelihood of skipping. Examining variations in the degree to which people adapt their behavior based on how much they enjoyed the prior trial can provide additional insight into the computational processes that drive abnormalities in decision-making. Poor behavioral adaptation to reward consequences may contribute to persistent and repetitive thoughts and behaviors despite negative consequences (Chamberlain et al., 2021; Verharen et al., 2020).

Decision-Making Patterns in OCPD, OCD, and AN

Examining decision-making in OCPD through the Web-Surf Task may assist in better understanding the mechanistic links to rigidity in OCD and AN. Our prior pilot data has uncovered distinct decision-making patterns in AN that may contribute to the rigidity typical of this disorder, including the dogged pursuit of weight loss despite negative consequences inherent to AN. While intolerance of uncertainty is a quality shared by both OCD and AN, those with AN may aim to reduce uncertainty via engaging in a narrow set of rule-governed eating behaviors (Brown et al., 2017) rather than the increased information-gathering and checking behavior seen in OCD. Accordingly, on the Web-Surf task, individuals with AN have demonstrated heightened decisiveness, characterized by spending less time making decisions and watching videos during the task and, therefore completing a greater number of trials (i.e., having more opportunities for reward) (Calvin et al., 2022; Haynos, Abram, et al., 2020). Similar rapid decision-making has been observed in AN during other neuroeconomic tasks and has been accompanied by decreased activity in brain areas related to executive functioning, signaling that this strategy may be less computationally demanding than deliberating over the optimal choice (King et al., 2016). Choice selectivity is also increased in AN on Web-Surf; individuals with AN showed lesser willingness to stay on video choices in which the category was less preferred or the delay was longer (Haynos et al., in prep), possibly reflecting an implicit preference for predictable versus unpredictable rewards seen in AN (Haynos, Lavender, et al., 2020). Although this pilot study did not directly examine behavioral adaptation on the Web-Surf task, prior research has demonstrated that individuals with AN struggle to update their behavior based on novel information (Keegan et al., 2021). These results explain the rigid focus on a fixed set behaviors seen in AN. When losing weight is established as the most preferred and rewarding outcome, an individual with AN may decisively pursue this goal by choosing to invariably and continuously engage in weight loss behaviors, rather than pursuing other sources of reward, despite harmful repercussions.

In contrast, the rigid behaviors of OCD, including repetitive actions, checking, and adherence to strict rituals can be understood to represent a pathological deficit in decisiveness (Sachdev & Malhi, 2005). Heightened intolerance of uncertainty in OCD has been found to result in signs of indecisiveness, such as slower processing speed and prolonged periods of information gathering prior to making decisions; this relationship strengthens as outcomes become more ambiguous (Hauser, Moutoussis, Iannaccone, et al., 2017; Hauser, Moutoussis, NSPN Consortium, et al., 2017; Mandali et al., 2019). This assertion is supported by abnormally increased activation in the orbitofrontal cortex and anterior cingulate cortex—subregions of the prefrontal cortex implicated in information gathering processes—leading to excessive caution and indecision in decision-making (Sachdev & Malhi, 2005). Similarly, individuals with OCD have been demonstrated to show heightened exploratory behavior, which may be indicative of low choice selectivity (Hauser, Iannaccone, et al., 2017; Kanen et al., 2019; Marzuki et al., 2021). These behaviors can be costly and impairing, especially when time is limited, as they result in repeatedly engaging in behaviors that provide low benefit. Adaptation of behavior over time is also impaired in OCD. Individuals with OCD will continue to rigidly prioritize certain choices, such as performing a ritual, despite experiencing negative outcomes (Luo et al., 2020; Nielen et al., 2009) and struggle to integrate new contextual information in order to “override” outdated associations between actions and outcomes (O’Brien et al., 2019; Rotge et al., 2015). Together, these findings suggest that those with OCD may engage in rigid behaviors such as checking because they are excessively and indiscriminately gathering information to reduce uncertainty, and not learning from the outcomes of their actions over time. During a time-limited foraging task like Web-Surf, rigid behavior may manifest in individuals with OCD as completing fewer trials because they are spending more time in the “offer zone” across trials, displaying decreased choice selectivity, and delayed behavioral adaptation.

Statement of the Problem

OCPD is a highly prevalent and debilitating mental disorder that is poorly understood, and current interventions fall short in addressing its defining feature of rigidity. While rigidity is a transdiagnostic feature shared with other disorders like OCD and AN, these disorders appear to be distinguished from one another by different underlying mechanisms leading to rigidity, which likely necessitate distinct treatments. Very little is known about the mechanisms leading to rigidity in OCPD. Therefore, examining potential decisional dysfunctions in OCPD, and how they related to the existing literature on other disorders (e.g., OCD, AN) promises to improve mechanistic models of OCPD. Improved knowledge of mechanisms will assist in improving treatment options for this currently under-served disorder.

This study joins the small but growing body of literature examining the underlying cognitive and neurobiological correlates of OCPD traits, and attempts to further specify its shared and distinct mechanistic processes in relation to the literatures on both OCD and AN. To do this, we focus on uncovering patterns in decision-making that lead to rigidity in individuals with elevated characteristics of OCPD, and compare our findings to extant knowledge of decision-making in OCD and AN. In addition, this study will be the first to our knowledge to explore whether specific OCPD trait domains are differentially related to alterations within the reward-based decision-making process.

Aims and Hypotheses

Due to the current lack of robust etiological and mechanistic models of OCPD, this study uses a strong inference method (Platt, 1964) to compare our findings against two competing theories informed by existing literature. By contextualizing our findings in relation to better-understood disorders that may both be related to OCPD, we can better characterize the observed mechanisms leading to rigidity in OCPD.

Aim 1: Characterize the processes related to choice decisiveness leading to rigidity across the spectrum of OCPD traits.

Hypothesis 1a: If OCPD shares decision-making processes with OCD, higher OCPD traits will be associated with a lower number of trials completed and a greater portion of task time spent making choosing and waiting for videos. These findings will reflect lower choice decisiveness among individuals with higher in OCPD traits.

Hypothesis 1b: If OCPD shares decision-making processes with AN, higher OCPD traits will be associated with a higher number of trials completed and a lesser portion of task time spent choosing and waiting for videos. These findings will reflect higher choice decisiveness among individuals with higher in OCPD traits.

Aim 2: Characterize the processes related to choice selectivity leading to rigidity across the spectrum of OCPD traits.

Hypothesis 2a: If OCPD shares decision-making processes with OCD, higher OCPD traits will be associated with a greater willingness to stay on video offers, including those with longer delays and from less preferred categories. These findings would reflect lower choice selectivity among individuals with higher in OCPD traits.

Hypothesis 2b: If OCPD shares decision-making processes with AN, higher OCPD traits will be associated with a decreased willingness to stay on video offers, including those with longer delays and from less preferred categories. These findings would reflect higher choice selectivity among individuals with higher in OCPD traits.

Aim 3: Determine the behavioral adaptation patterns leading to rigidity across the spectrum of OCPD traits.

Hypothesis 3: Higher OCPD traits will be associated with less adaptation in stay/skip decisions based on the amount of enjoyment reported in the previous trial, reflecting low behavioral adaptation. This pattern is considered to be indicative of behavioral rigidity, regardless of if OCPD shares decision-making processes with AN or OCPD.

Aim 4: Explore whether choice decisiveness, choice selectivity, and behavioral adaptation are associated with specific OCPD trait domains.

As these analyses are exploratory, we do not propose a priori hypotheses.

Method

Participants

Participants are from a community sample of 88 adult participants who were originally recruited for a cross-sectional study investigating decision-making profiles in individuals with and without characteristics of work addiction. Individuals who were under 18 years of age, unable to read or write in English, did not have capacity to provide informed consent, or were not currently working full-time (defined as < 30 hours/week) were excluded from participation in this study. Although the study was adequately powered for its originally intended analysis, an a priori power analysis was not conducted for this secondary analysis. However, the intended analyses for this study have yielded adequately powered results in prior investigations with fewer participants (Haynos et al., in prep). Five participants were excluded for the purposes of this analysis due to excess missing data on either the FFOCI-SF or Web-Surf task. Our final sample of participants (*N* = 83) ranges in age from 19 to 61 years (*M* = 33.18, *SD* = 9.07). Sample characteristics are described in **Table 1**.

Procedures

Data were obtained between May 2020 to September 2022. Participants were recruited through advertisements within the local campus and community surrounding University of Minnesota and on social media. Participants provided written informed consent prior to study procedures. An initial online survey for screening was administered, after which eligible participants attended a 2-hour remote study visit that involved completing the virtually-delivered Web-Surf task, questionnaires, and a diagnostic interview with trained research staff. All procedures occurred remotely using HIPAA-approved data collection platforms. Efforts were taken to ensure reliability in remote data collection, including instructing participants to complete participation in a secure location with strong internet connectivity, and to avoid engaging in competing behaviors (e.g., looking at their phone or another internet tab) when completing research activities. Task completion was proctored by research staff to ensure attention remained fixed on the task and that any questions or issues with the task were handled expediently. Participants were compensated for their time. Only one previous analysis of this dataset has been conducted previously, which examined whether OCPD traits moderated the relationship between temporal discounting and mental health and quality of life outcomes. The hypotheses of the original study have not yet been examined. Neither set of analyses overlaps with the planned analyses for this study.

Measures

Demographic and Clinical Measures

As part of the study assessments, participants were asked questions regarding their age, sex assigned at birth, gender identity, racial and ethnic identity, sexual orientation, educational attainment, household and personal income, relationship status, and number of children. Additionally, information regarding employment was collected including work or student status, job title and industry, and hours worked per week. This information will be used for descriptive purposes to characterize our sample and will not be used in our primary or exploratory analyses.

Psychiatric Diagnosis. The Adult Mini-International Neuropsychiatric Interview (MINI) is a brief structured diagnostic interview for major psychiatric diagnoses in the DSM-5 (Sheehan et al., 1998). This assessment was administered by a trained assessor during the in-person study visit. Participants were also asked to self-report any current or past psychiatric diagnoses and/or treatments. This information will be used for descriptive purposes to characterize our sample and will not be used in our primary or exploratory analyses.

Five-Factor Obsessive Compulsive Inventory—Short Form (FFOCI-SF)

OCPD traits were measured using the FFOCI-SF, a dimensional measure of traits associated with obsessive-compulsive personality disorder based on the Five-Factor Model of personality (Griffin et al., 2018). Across 48 items, the FFOCI assesses 12 maladaptive OCPD traits (defined in **Table 2**), each consisting of 4 individual items scored on a 5-point Likert-type scale and summed to obtain the domain score. Response options range from 0 = false/strongly disagree to 5 = definitely true/strongly agree. Domain scores showed acceptable to good reliability (α range = .67-.84). In addition to individual domain scores, the summed total score provides an overall measure of OCPD trait severity (α = .93). Possible total FFOCI scores range from 48-240; total scores in our sample range from 86-206 (*M* = 152.35, *SD* = 26.61), suggesting adequate range and spread of FFOCI scores to ensure variability in this predictor.

Neuroeconomic Paradigm

Web-Surf Task. The Web-Surf task was adapted from the "Restaurant Row" foraging paradigm used with rats, and developed as a translational measure of decision-making in humans (Abram et al., 2016). During the Web-Surf task, "surfing" the Web for pleasant videos is akin to foraging for valuable resources. Participants spend 30 minutes navigating through four video galleries (humorous bike accidents, dance, landscapes, kittens; see Figure 1), each of which presented a clip from one of four categories. Before "entering" each gallery, participants are informed of the category of video and a random wait time, between 3 and 30 seconds, before they are able to watch the video—this is referred to as the "offer zone". Participants then decide whether they way to "stay" (wait for the current reward) or "skip" (move to the next gallery without entering the current gallery), which requires them to consider the costs of the delay against the putative reward associated with the video category. After viewing a video, participants rate their liking of the video on a scale from 1 (extremely dislike) to 5 (extremely like). They then "travel" to the next gallery by clicking several buttons corresponding to numbers randomly positioned on the screen. Participants complete as many trials as they are able to within the 30-minute period.

Task-Derived Metrics. The category rank variable will be computed by ranking each category of video from 1-4 based on how many videos the participant viewed in each category. When ties occur between two categories, random assignment between the two subsequent orders (e.g., rank 1 and 2) will occur to avoid systematic bias. Proportion of task time spent in each aspect of the trial (i.e., decision-making, watching videos, traveling) will be calculated by summing the cumulative time spent in each aspect of the trial across all trials for a given participant and dividing this number by the total run time of the task. For the calculation of total trials completed, there were a percentage of participants that encountered technical problems with the remotely-delivered task that prevented them from completing all potential trials. Therefore, participants will be coded as having complete or incomplete data and this variable will be entered as a covariate in certain models as described below.

Data Analyses

Analytic Plan

Aim 1: Characterize the processes related to choice decisiveness leading to rigidity across the spectrum of OCPD traits.

A Pearson correlation will be calculated to determine the relationship between OCPD traits and number of trials completed throughout the task, only including participants with complete trial data. The proportion of task time spent choosing videos, waiting for videos, rating videos, and traveling between trials will be calculated by dividing reaction time for each element by total reaction time for each participant. Binomial regressions will be run to predict the proportion of time spent on each task element. OCPD traits will be entered as a predictor in these models and the number of trials and completeness will be covariates. Proportion of task time spent choosing whether to stay or skip will indicate decisiveness (i.e., a greater proportion of time spent choosing relative to other activities indicates lower decisiveness, while a lower proportion of time spent choosing indicates greater decisiveness).

Aim 2: Characterize the processes related to choice selectivity leading to rigidity across the spectrum of OCPD traits.

A generalized linear mixed model will be run to predict the likelihood of choosing to stay on or skip a video across trials. OCPD traits, delay time, and category rank of the video, as well as the interactions between these variables will be examined as independent variables. Trial number and completeness will be entered as covariates and analyses will control for within-subject variance as a random effect. This analysis will allow us to examine the degree to which probability of staying and viewing is dependent upon OCPD traits and if this relationship is conditioned by the delay they need to wait through and how much they like a particular video. Greater choice selectivity will be operationalized as a lower likelihood of choosing to stay on a video, especially under conditions of greater delay and lower category rank.

Aim 3: Determine the behavioral adaptation patterns leading to rigidity across the spectrum of OCPD traits.

Cross-lagged generalized linear models will be conducted in which past-trial enjoyment rating for a given category, OCPD scores, and their interaction will serve as independent variables, number of trials and completeness will be covariates, and choice (stay/skip) will serve as the dependent variable, with subject ID entered as a random effect. The degree to which past-trial enjoyment influences the subsequent choice to stay or skip will be indicative of the behavioral adaptation process in sequential decision-making.

Exploratory Aim 4: Explore whether choice decisiveness, choice selectivity, and behavioral adaptation are associated with specific OCPD trait domains.

All of the above analyses will be repeated, but will substitute specific OCPD domain scores instead of overall OCPD traits, in order to determine if specific facets of OCPD may be especially predictive of aspects of behavioral rigidity.

Missing Data

Cases were excluded from the analysis who were missing data for all or most of the variables of interest (Web-Surf, FFOCI-SF). Our remaining sample had <5% data missing at random. We used the Multivariate Imputation by Chained Equations (MICE) protocol to impute missing item-level data for numeric, non-demographic variables (Raghunathan et al., 2000; van Buuren & Groothuis-Oudshoorn, 2011). Of note, skip logic within the task results in meaningful missing data for certain trials (i.e., no video ratings are provided when the participant chooses to skip to the next trial because they have not viewed the video associated with the trial). Such meaningful missingness was not imputed.

Results

Table 1 presents demographic and clinical characteristics of the sample. Participants (*N* = 83) ranged from 19-61 years old, with an average age of 33.18 years. A majority were cisgender women (62.7%), white (66.3%), and heterosexual (73.5%). Our sample was highly educated, with 88% holding a bachelor's degree or higher, and most (89.2%) reported being currently employed full-time.

Preliminary Data Analysis and Data Transformations

To ensure data quality, descriptive statistics of our study variables were computed and are presented in **Table 3**. Visual inspection of histograms and boxplots for each outcome variable indicated presence of significant outliers (defined as > 3 SD from mean) in choice reaction time, rating reaction time, and transit reaction time. As these likely indicated user error or distraction during the Web-Surf task, these outliers were removed at the trial level. No outliers were identified in the delay reaction time variable.

To calculate proportions for each reaction time variable, each participant's times per trial dedicated to each element were summed over their entire task duration to obtain overall reaction times dedicated to choice, delay, rating, and transit. Proportions were calculated by dividing each summed reaction time of an element by the participant's total reaction time (all reaction time elements summed). Visual inspection and normality testing revealed significant skewness for proportion of time in transit (skew = 2.45) and in delays (skew = -2.66). To address this, these variables were log-transformed and a constant was added to remove negative values to ensure model fit in the subsequent regression models. For the mixed effects models, all continuous predictor variables were z-scored in order to support model convergence.

An additional exploratory analysis was conducted to determine whether comparing a subset of participants with the most elevated OCPD traits to the remainder of the sample yielded different results. Participants were divided into groups defined as high OCPD traits (top 25% of FFOCI-SF scores) and low OCPD traits (bottom 75% of FFOCI-SF scores). This categorical measure of OCPD traits was then entered as a predictor in our models in place of the continuous FFOCI-SF score.

Choice Decisiveness

Aim 1 was to determine the relation between OCPD traits and choice decisiveness by examining whether FFOCI total score predicted overall trials completed and proportion of task time spent choosing and waiting for videos. For this aim, we expected greater choice decisiveness to be represented through a higher number of trials completed (because participants would be completing each individual trial more quickly) and a lower proportion of time dedicated to choosing and waiting for videos. A Pearson correlation between OCPD traits and number of trials completed throughout the task revealed no significant association, $R = -.15$, 95% CI [-.28, .09], $p = .211$. Results from binomial regressions (**Table 4**) indicated that OCPD traits, measured continuously did not predict proportion of time spent choosing videos ($p = 0.982$), rating videos, ($p = .536$), traveling between offer zones ($p = .803$), or waiting during delays ($p = .893$). We did, however, observe a significant difference in number of trials completed between low OCPD (M = 111.13) and high OCPD (M = 116.90), $t(6774) = -4.57$, 95% CI [-8.24, -3.29], $p < .001$. Results from binomial regressions (**Table 4a**) indicated that those with high OCPD traits spent significantly less time choosing ($p < .001$) and traveling ($p < .001$) over the course of the task than those with low OCPD traits.

For our exploratory hypothesis, this analysis was repeated with each FFOCI domain subscale (neuroticism, extraversion, openness, and conscientiousness) as a predictor. A significant correlation was found between openness and number of trials completed, such that higher severity of OCPD openness-related traits (e.g., restricted emotions, behavioral and moral rigidity) was associated with a fewer number of trials completed, $R = -.27$, 95% CI [-.48, -.04], $p = .023$, or less decisiveness. However, when controlling for number of trials completed and completeness of data, none of the domains were significant predictors of any of the reaction time elements (**Table 4b**).

Choice Selectivity

Aim 2 was to determine the relation between OCPD traits and choice selectivity by examining whether FFOCI total score predicted willingness to stay on video offers. For this hypothesis, we expected greater choice selectivity to be represented through more sensitivity to delay (choice cost) and category rank (choice reward) characteristics when deciding to stay and watch or skip videos.

Delay Time as Predictor

When controlling for trial number and data completeness, delay time was a significant predictor of choice, such that longer delays predicted less likelihood of staying across the sample (B = -0.54, SE = 0.03, $p < .001$), confirming the validity of the task (**Table 5**). No significant main effect of OCPD traits was observed when measured continuously (B = 0.09, SE = 0.16, p = .583) and no significant interaction was noted between OCPD traits and delay time (B = 0.05, SE = 0.03, p = .068). The interaction between OCPD traits measured categorically and delay time was significant, with high OCPD traits significantly more likely to stay when faced with longer delays (B = 0.16, SE = 0.06, p = .016) (**Table 5a**).

For our exploratory aim, OCPD trait domains were entered as predictors in place of overall OCPD traits (**Table 5b**). Results indicated that the trait domain of openness predicted likelihood of staying (B = 0.33, SE = 0.16, p = .037) such that low openness predicted greater willingness to stay across trials (i.e., less selectivity); however, this relationship was not significant after controlling for multiple comparisons. Further, neuroticism significantly moderated the relationship between delay time and choice (B = -0.06, SE = 0.03, p = .016), such that longer delays predicted lower likelihood of staying (i.e., more selectivity) for those high in neuroticism. In contrast, for those high in conscientiousness, *shorter* delays predicted lower likelihood of staying (B = 0.07, SE = 0.03, $p = .008$), representing greater selectivity, but in the opposite direction than anticipated (i.e., greater desire for videos requiring a longer delay).

Video Category Rank as Predictor

Category rank was also a significant predictor of choice across participants (**Table 5**), such that higher-ranked categories predicted greater likelihood of staying ($\chi^2(3, N=82) = 1498.75$, $p < .001$), confirming the validity of the task. No significant main effect of OCPD traits was observed (B = 0.27, SE = 0.21, $p = .199$). However, a significant effect was found for the interaction of OCPD traits and category rank, suggesting that those with higher OCPD traits were less likely to stay on less preferred videos versus more preferred videos compared to those with lower OCPD traits ($\chi^2(3, N=82) = 11.68$, $p = .009$). Post hoc contrasts between pairs of category ranks revealed a significant difference in effect size between category ranks 1 and 3 (B = 0.30, SE = 0.10, $p = .022$) and between ranks 2 and 3 (B = 0.22, SE = 0.08, $p = .045$). This indicates greater selectivity in choice, such that higher OCPD traits predicted greater likelihood of staying on their most preferred videos, but lower likelihood of staying on their least preferred videos. This pattern was also observed when comparing high and low OCPD traits (**Table 5a**); those with the highest OCPD traits were significantly more sensitive to category rank when choosing ($\chi^2(3, N=82) = 12.38$, $p = .006$).

The interaction between OCPD trait domains and category rank in predicting choice was also examined as part of our exploratory aim (**Table 5c**). Conscientiousness (e.g., perfectionism, workaholism, doggedness) predicted a significantly greater choice selectivity based on category rank ($\chi^2(3, N=82) = 24.55$, $p < .001$). Post-hoc contrasts revealed significant differences in effect between category ranks 1 and 3 (B = 0.28, SE = 0.10, $p = .037$), ranks 1 and 4 (B = 0.36, SE = 0.11, $p = .008$), ranks 2 and 3 (B = 0.31, SE = 0.08, $p < .001$), and ranks 2 and 4 (B = 0.39, SE =

0.09, $p < .001$). Extraversion was also a moderator of the relationship between category rank and choice ($\chi^2(3, N=82) = 19.36$, $p < .001$); higher severity of OCPD extraversion-related traits (e.g., detached coldness, risk aversion) predicted greater selectivity between more- and less-preferred categories. Significant differences in effect of extraversion were found between category ranks 1 and 2 (B = 0.42, SE = 0.11, $p < .001$), ranks 1 and 3 (B = 0.33, SE = 0.11, $p = .016$), and ranks 2 and 4 (B = -0.27, SE = 0.10, $p = .025$). No other significant contrasts were present (ps > .185). These findings indicate that higher extraversion- and conscientiousness-related OCPD traits predicted greater sensitivity to category rank (i.e., more selectivity) when making choices.

Behavioral Adaptation

Aim 3 was to determine the influence of OCPD traits on behavioral adaptation through examining the effect of previous-trial enjoyment rating on subsequent choice to stay/skip at the next trial within a given genre. For this aim, we hypothesized that less behavioral adaptation would be reflected through lower influence of past-trial rating on subsequent choice. Unsurprisingly, higher past-trial enjoyment ratings significantly predicted choice to stay across participants (B = 0.99, SE = 0.06, $p < .001$), confirming the validity of the task. OCPD traits, measured continuously, significantly moderated the relationship between past-trial ratings and choice (B = 0.21, SE = 0.05, $p < .001$) such that higher OCPD scores predicted greater likelihood of staying on videos that were previously highly rated, suggesting a greater degree of behavioral adaptation in those with higher OCPD scores (**Table 6**). This pattern was also observed when comparing high and low OCPD traits; categorical OCPD traits significantly moderated the relationship between past-trial ratings and choice (B = 0.65, SE = 0.16, $p <.001$) (**Table 6a**).

An additional exploratory analysis was conducted to control for the influence of category rank on the relationship between past-trial rating and choice. This analysis was conducted to ensure that the results reflected behavioral adaptation, rather than simply a greater tendency to stay on more preferred and skip less preferred videos. In this model, category rank remained a significant predictor of choice (χ^2 (3, *N*=82) = 291.05, $p < .001$) and the moderation effects of OCPD traits remained significant (χ^2 (1, *N*=82) = 5.38, $p = .020$), suggesting that the results did indicate more behavioral adaptation for those with higher OCPD traits.

For our exploratory aim 3, we examined specific OCPD trait domains as moderators of the relation between past-trial ratings and choice to stay or skip (**Table 6b**). Significant moderation effects were observed for neuroticism (B = 0.12, SE = 0.06, $p = .031$), extraversion (B = 0.11, SE = 0.05, $p = .028$), and conscientiousness (B =.0.23, SE = 0.05, $p < .001$); only the effect of conscientiousness remained significant after correction for multiple comparisons. There was a significant main effect of openness on choice (B = 0.37, SE = 0.18, $p = .036$) – higher severity of OCPD openness-related traits predicted greater willingness to stay across trials - but this result was no longer significant following correction for multiple comparisons. Further, the interaction between openness and past-trial ratings was not significant ($p = .080$). These results reveal that the observed effect of OCPD scores on behavioral adaptation is primarily driven by high conscientiousness.

Discussion

The present study sought to characterize the mechanistic substrates underlying rigidity in OCPD through a novel neuroeconomic task. To do this, we examined how OCPD traits contributed to specific components of sequential decision-making (choice decisiveness, choice selectivity, and behavioral adaptation) that could lead to behavioral rigidity. We aimed to contextualize our findings within the existing literature by comparing them to extant knowledge about decision-making processes in AN and OCD in order to identify shared and distinct mechanistic processes between different clinical presentations. While these two psychiatric disorders are similarly characterized by cognitive and behavioral rigidity, those with AN have shown more decisiveness and selectivity in decision-making, swiftly and narrowly seeking out only their most preferred outcomes (Calvin et al., 2022; Haynos, Abram, et al., 2020). On the other hand, evidence suggests that those with OCD may show more indecisiveness and less selectivity in decision-making, being over-deliberative and over-sampling available options (Hauser, Iannaccone, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017; Kanen et al., 2019; Marzuki et al., 2021). Comparing decision-making patterns observed in those with elevated OCPD traits to those in AN and OCD offers the possibility of improving the precision of the mechanistic models of OCPD, as well as transdiagnostic models of rigidity. Further, this approach can inform improvements to interventions for this currently under-treated disorder by drawing off of therapeutic approaches for treating AN and OCD. In addition, we explored whether the individual OCPD trait domains of neuroticism, extraversion, openness, and conscientiousness differentially contributed to decision-making outcomes, in alignment with the trait-driven alternative model of personality disorders.

Choice Decisiveness

Individuals with different psychiatric disorders vary in choice decisiveness, or the efficiency with which they make decisions (Scholl & Klein-Flügge, 2018). Greater efficiency often suggests a reliance on less computationally intensive processes, whereas lesser efficiency reflects engaging more cognitively taxing strategies. Imbalances in either direction may lead to enhanced rigidity. Thus, we hypothesized that OCPD traits would be significantly related to choice decisiveness, predicting either more rapid decision-making as observed in AN or slowed decision-making as observed in OCD. However, our analysis revealed no association between severity of OCPD traits, when measured continuously, and our markers of decisional efficiency (i.e., number of trials completed or proportion of time spent choosing and waiting for videos). The subset of individuals with the most elevated OCPD traits, though, did spend significantly less time than other participants making choices and traveling between trials over the course of the task, which ultimately allowed them to complete a greater number of trials. Thus, at their greatest severity, OCPD traits did appear to predict choice decisiveness, which may be a pathway to rigidity in this group.

Our results are inconsistent with the heightened deliberation that has been previously observed in OCPD during an executive planning task (Fineberg et al., 2015), but this may be at least partly attributed to differences in sampling and design between studies. However, it is also possible that heightened deliberation in OCPD may emerge in the face of more cognitively demanding tasks, but may not apply to reward-based decision-making. These findings may suggest that, at clinically significant levels, over-decisiveness emerges from OCPD traits that aligns with the patterns observed in AN (Calvin et al., 2022; Haynos, Abram, et al., 2020; King et al., 2016), but deviates from the patterns expected in OCD (Hauser, Iannaccone, et al., 2017; Hauser, Moutoussis, Iannaccone, et al., 2017; Mandali et al., 2019; Pushkarskaya et al., 2017). Thus, the findings of this aim indicate that decision efficiency could be mechanism of rigidity in OCPD, and offer some preliminary evidence of a shared mechanism between OCPD and AN that may not be observable at sub-clinical levels.

Choice Selectivity

With regard to choice selectivity, we hypothesized that OCPD traits would be significantly associated with willingness to sample videos across a range of delay times (costs) and video categories (rewards) presented in the task. Lesser willingness to sample videos across a variety of costs and rewards could contribute to rigidity through a rule-based process whereby participants narrowly focused on only the least costly and/or most highly desired rewards. However, greater willingness to sample across different costs and rewards could also contribute to rigidity through a repetitive process of testing choices without learning from their consequences. We evaluated two competing predictions: that those higher in OCPD traits would be willing to pursue only the most rewarding and low-cost options, as seen in AN (i.e., greater value-congruence or exploitation; Hagan et al., 2024; Haynos et al., in prep), or that they would show heightened willingness to explore less-preferred or higher-cost options despite having limited time, as seen in OCD (i.e., greater sampling or exploration; Cillo et al., 2019; Marzuki et al., 2021).

Selectivity Related to Cost

Results indicated that overall OCPD traits, when measured continuously, did not predict greater or lesser selectivity related to delay time, meaning that those high in OCPD traits tolerated long delays to the same degree as those low in OCPD traits. However, when examined categorically, those with the highest OCPD traits did show a significantly greater tolerance for longer delays than other participants. That those highest in OCPD traits showed greater delay tolerance on this task seems to replicate previous research suggesting less delay discounting (i.e., higher tolerance of delayed reward) in OCPD compared to healthy controls (Pinto et al., 2014). However, it is important to note that this previous study assessed delay discounting through an intertemporal choice task comparing hypothetical monetary rewards, wherein waiting through a delay would result in a larger reward. In contrast, while the Web-Surf task also assesses intertemporal choice, the sequential and time-limited component of the task means that waiting through a longer delay incurs a cost that directly lessens one's ability to obtain future rewards.

This element may explain why despite those with AN and OCPD displaying similar shallow delay discounting on traditional intertemporal choice tasks (Lempert et al., 2019; Pinto et al., 2014), those with AN appear to prefer shorter delays when assessed using the current paradigm (Haynos et al., in prep). Our findings do not indicate that, at subclinical levels of OCPD, one's sensitivity to cost during sequential decision-making underlies rigidity in subclinical OCPD; however, a diminished sensitivity to cost may emerge at clinically significant levels. In comparison to the heightened selectivity observed in AN in choosing only low-cost options (Haynos et al., in prep) or the decreased selectivity resulting in engagement in costly behaviors expected in OCD (Dubois & Hauser, 2022), results point to a potential shared mechanism of lower selectivity related to cost underlying rigidity in OCPD and OCD.

Selectivity Related to Reward

When examining choice selectivity related to reward, we did observe a significant effect even at the subclinical level: higher OCPD traits predicted significantly greater sensitivity to category rank when examined both continuously and categorically. This suggests that those with greater OCPD traits demonstrated lower willingness to watch videos from their least-preferred categories, but heightened willingness to watch videos from their most-preferred categories. This pattern is suggestive of a narrow focus on pursuing only the most rewarding or "successful" outcomes. A similar tendency for over-exploitation has been observed in other psychiatric concerns such as addiction (Addicott et al., 2017), and suggests that preference for predictable over unpredictable rewards may be a shared mechanism between OCPD and AN (Haynos, Lavender, et al., 2020). As major clinical features of OCPD include rigid perfectionism and intolerance of mistakes (Pinto et al., 2022), the selectivity we observed may reflect the tendency for those with OCPD to only engage in tasks where there is a high probability of reward attainment and neglect efforts towards more uncertain outcomes.

Behavioral Adaptation

It was predicted that OCPD would be associated with deficits in adjusting behavior over time in response to previous outcomes, mirroring the impairment in behavioral adaptation that appears to be a shared feature of both AN (Keegan et al., 2021) and OCD (O'Brien et al., 2019; Rotge et al., 2015). We observed that the degree of behavioral adaptation in response to previous reward was significantly affected by OCPD traits when measured both continuously and categorically, but contrary to our hypothesized direction. Instead of engaging in an unchanging, rule-based pattern of behavior seen in AN or showing impaired learning from new information seen in OCD, those with higher OCPD demonstrated *greater* behavioral adaptation and thus more quickly adjusted choices in response to previous outcomes. It is worth highlighting that we can currently only estimate how individuals with AN and OCD would behave on this metric based on similar literature, as behavioral adaptation during Web-Surf has not yet been measured in these populations. Thus, it is possible that those populations would behave differently on this task than our hypothesis suggests.

While previous studies utilizing neuropsychological set-shifting tasks identified deficits in behavioral adaptation associated with OCPD (Fineberg et al., 2015; García-Villamisar & Dattilo, 2015), the findings of our study suggest that behavioral adaptation to *reward-based* decision-making processes may be intact and even overactive in this population. Our observation sheds light on how rigidity in OCPD may be a result of "hyper-economical" decision-making which is highly sensitive to even a single instance of reduced (or heightened) reward, after which the likelihood of choosing a similar option again sharply decreases (or increases). Clinically, this pattern may underlie a number of common symptoms of OCPD, causing dysfunction in identity and interpersonal relationships. For example, those with OCPD may be so focused on perfection that they quickly decide to quit or abandon a task if they cannot immediately master it. Harsh criticism of others' mistakes may arise from this heightened sensitivity to reduced reward, where an individual with OCPD may be unwilling to engage in empathy or tolerate giving someone else a "second chance" after a single misstep (Cain et al., 2015; Pinto et al., 2022). The inverse effect can also be seen: following a heightened experience of reward (e.g., being praised for increased productivity at work), those with OCPD may become "stuck" in rigid patterns in pursuit of this reward (e.g., work addiction and perfectionism). Taken together with our previous finding of decreased cost sensitivity, this "hyper-economical" pursuit of reward may persist even when this comes at the cost of completing tasks and maintaining relationships (Atroszko et al., 2020).

Of note, our finding could reflect a greater sensitivity to reward prediction error (RPE, i.e., earning a greater or lesser reward than predicted; Schultz et al., 1997) in OCPD. Initial evidence suggests heightened brain activity in adolescents with AN associated with RPE, corresponding with higher illness severity (DeGuzman et al., 2017). In contrast, individuals with OCD show a blunted neural response to RPE, which may underlie deficits in reinforcement learning (Gründler et al., 2009). Future research can provide additional clarity regarding the relationship of OCPD, AN, and OCD by examining RPE in those with OCPD via behavioral tasks and neuroimaging.

Insights Into Mechanistic Overlaps Between OCPD, OCD, and AN

Our findings offer several important implications regarding the degree to which mechanisms of rigidity may be shared versus distinct across disorders. First, it is of particular interest that elevated OCPD traits resembled expected patterns in OCD only with regard to choice selectivity related to cost. Historically regarded as highly similar or even overlapping disorders, some recent literature questions the relationship between the two (Starcevic & Brakoulias, 2014; Taylor et al., 2011). Our results build on previous literature indicating important mechanistic differences between OCD and OCPD despite many similarities in clinical characteristics (Luo et al., 2020; Marincowitz et al., 2021; Pinto et al., 2014). Second, we identified several mechanistic overlaps between OCPD traits and AN, such that these presentations may share a pathway to inflexible behavior characterized by heightened choice decisiveness and selectivity related to reward. This suggests that similar to AN, the psychopathology characteristic of OCPD may arise from under-deliberation and narrow reward preferences. Third, we identified a component of decision-making that may differentiate OCPD traits, AN, and OCD—namely, behavioral adaptation. Overall, the current study highlights how while some mechanisms may be shared with AN and OCD, others may be distinct to OCPD. The intricate nature of these findings demonstrates the value of taking a fine-grained approach to examining computational processes across psychiatric disorders, which provides a more precise focus for future intervention research. While the three disorders share an outward presentation of rigid thinking and behavior, a clearer etiological picture emerges when each is examined through a decision science lens, showing evidence of related yet distinct combinations of impaired decision-making processes.

Impact of Trait Domains on Decision-Making

As an exploratory aim, we examined the contribution of OCPD symptoms within each of the four trait domains, measured continuously, to our outcomes of interest. We found that neuroticism significantly impacted choice selectivity related to cost, such that longer delays were considered less tolerable by those with the excessive worry captured by this trait. The relationship between neuroticism and impatience has been previously demonstrated (Manning et al., 2014) and may reflect efforts to alleviate or avoid negative affect associated with incurring a cost by avoiding a delayed reward (Augustine & Larsen, 2011). Traits within the conscientiousness domain, such as perfectionism, concern about detail, rule adherence, self-discipline, and rumination, were major drivers of both cost- and reward-related choice selectivity. Specifically, conscientiousness traits predicted *higher* tolerance of longer delays but a greater sensitivity to category rank when choosing, suggesting a preference towards larger rewards following a delay rather than immediate, but smaller, gratification. Behaviorally, this may manifest in a propensity to rigidly pursue rewards without consideration of associated costs. This mirrors the pattern seen in individuals with AN (Haynos, Lavender, et al., 2020) as well as those with a clinical diagnosis of OCPD (Pinto et al., 2014), and may reflect the shared core trait of conscientiousness that characterizes both disorders, but not OCD (Halmi et al., 2005). The opposing influences of neuroticism and conscientiousness on delay tolerance has been supported by a previous neuroimaging study in individuals without psychiatric concerns (Manning et al., 2014), and this may explain why we failed to observe a significant effect on choice selectivity when these domains were considered together. Conscientiousness was also a significant predictor of behavioral adaptation in response to liking over the course of the task, indicating that this trait is a main driver of the heightened response to reward feedback observed in OCPD.

Extraversion-related OCPD traits, for which higher scores indicate greater interpersonal detachment and risk aversion, also predicted greater preference for watching videos only from the highest-ranked categories. Risk aversion may drive this observed effect, as choosing to stay on videos from lower-ranked categories may constitute a risk of loss of resources (e.g., time and enjoyment). Evidence that individuals with post-acute AN are also more risk averse, choosing the "safe" or more predictable option more often (Bernardoni et al., 2020; Haynos, Lavender, et al., 2020); thus, traits related to risk aversion may be responsible for shared mechanistic pathways to rigidity for AN and OCPD. Clinically, those with OCD also appear risk averse, but the literature is more mixed regarding risk aversion during decision-making tasks in this population, which may reflect the distinction between risk aversion (i.e., when outcome probability is known) and ambiguity aversion (i.e., when outcome probability is unknown) (Jacoby et al., 2023). Further, mechanisms of risk aversion observed during a gambling task, in which losses and gains are objective, may differ from risk aversion observed during a task in which reward is defined by subjective personal preferences. Findings from a direct comparison of decision-making under ambiguity versus risk suggest that those with OCD are similarly averse to both conditions, although it is unclear whether this was purely due to OCD or comorbid affective/anxiety symptoms (Jacoby et al., 2023). In the case of the present study, the risk aversion demonstrated by those high in OCPD traits most closely resembled that seen in AN.

Overall, the findings from our exploratory analyses shed light on the importance of considering a trait-based model when examining mechanisms of personality pathology. When parsing the syndrome of OCPD into its individual components, it becomes clear that different facets of this disorder may influenced by different decision-making dysfunctions, underscoring the necessity for interventions to attenuate rigidity by targeting these individual traits and their underlying distinct mechanisms. Specifically, the ubiquitous impact of conscientiousness on three outcomes of interest suggests that a trait typically regarded as adaptive can contribute to rigid, maladaptive functioning at extreme levels (Grant & Schwartz, 2011). That conscientiousness was such a strong predictor of rigidity during sequential decision-making suggests that individuals high in facets such as perfectionism, workaholism, doggedness, and attention to detail may be prone to negative outcomes when things like adherence to routines, productivity and thoroughness, and maintenance of order/cleanliness are disrupted.

Implications for Treatment of OCPD

Because it is poorly understood, research on effective treatment of OCPD has been stagnant and thus a strong, evidence-based psychotherapeutic treatment for this debilitating disorder remains elusive (Pinto et al., 2022). Outcomes of the current study can help to propel treatment research forward in several important ways. Reward preferences that are highly polarized lead to pursuit of activities that consistently yield reward—in AN, dietary restriction and weight loss; in OCPD, organization, work, saving money—in a narrow, inflexible, and ultimately maladaptive way. When this pursuit is disrupted—for example, due to a change in routine or another person's "mistake"—those with OCPD are highly vulnerable to experiencing distress and anger (Pinto et al., 2022). Further, over-decisiveness may compound this effect; other domains, such as rest, leisure time, or other pleasant activities may be neglected because they are experienced as less rewarding or not pursued at all. Given this finding, future research in OCPD treatment may benefit from a focus on interventions that attempt to target similar processes of reward sensitivity in AN. RO-DBT has increasingly been suggested as an intervention that may be helpful in treating AN, given its explicit targeting of "overcontrol" (Ben-Porath et al., 2020). In addition to a focus on social connectedness, RO-DBT seeks to address rigidity due to diminished reward sensitivity through increasing openness to new experiences and environments (Lynch et al., 2015). This is achieved via encouraging the individual to engage in experiences they would typically avoid and to practice flexibly altering behavior when it becomes counterproductive or harmful (Lynch et al., 2015). However, RO-DBT does not explicitly address the issue of *heightened* reward associated with disorder-congruent behaviors, and notably the literature on this treatment in AN remains limited.

Both cognitive-behavioral therapy (CBT) and its third-wave successor, acceptance and commitment therapy (ACT), have been explored as potential treatment options for OCPD. Non-controlled studies of CBT have provided some evidence for efficacy in OCPD (Enero et al., 2013; Strauss et al., 2006); however, it cannot be determined whether improvements were directly a result of CBT or other shared factors. Interestingly, results from a number of RCTs demonstrate that CBT is effective in treating “clinical perfectionism” occurring in the context of anxiety, depression, and eating disorders (Shafran et al., 2023). While CBT might benefit those with OCPD by decreasing self-criticism associated with perfectionism, it remains unclear whether it targets the specific mechanisms herein identified that lead to the core trait of rigidity. To date, there is no published data on the use of ACT to treat OCPD, though its focus on increasing psychological flexibility may be relevant to this type of psychopathology. *Defusion*, one of ACT’s “core flexibility processes,” focuses on decreasing fusion between thoughts and behaviors while increasing tolerance of nonrewarding or negative experiences (Luoma et al., 2017), which could in theory help to restore equilibrium to the reward processing system in OCPD (Pinto et al., 2022). As our results highlight that a prompt dismissal of nonrewarding experiences may be a key to rigidity in OCPD, this aspect of ACT may be especially well-suited to treating this disorder. To establish the utility of ACT for OCPD, pilot studies are necessary.

An alternative treatment that may be effective in targeting reward mechanisms in AN is Positive Affect Treatment (PAT). Originally developed to treat anhedonia in depression and anxiety, PAT aims to increase positive affect through behavioral activation coupled with recounting of positive affective experiences in session (Craske et al., 2016, 2019). Notably, PAT appears more effective in targeting aberrations in reward sensitivity than CBT aimed at reducing negative affect (Craske et al., 2019, 2023). Its adaptation for use in treating AN (PAT-AN) emphasizes increasing positive affect and reward specifically associated with non-disorder-related activities, while reducing positive affect and reward associated with disorder-congruent behavior (Haynos et al., 2021). Initial results from a pilot randomized controlled trial of PAT-AN demonstrate this treatment's potential to significantly decrease disordered behaviors and comorbid affective symptoms (Haynos et al., 2023). PAT for OCPD could replicate this approach by increasing positive affect associated with flexibility and leisure, while decreasing positive affect tied to behaviors like productivity and control. Considering the mechanistic overlaps in reward sensitivity demonstrated by the present study, the application of PAT to OCPD warrants attention through future research.

In contrast, we observed that individuals with OCPD traits deviated from expected patterns in both AN and OCD with regard to behavioral adaptation. These findings may provide insight into the dissimilarities between some of the mechanistic processes underlying these conditions, which may contribute to differences in clinical symptom presentations and thereby require alternative treatment approaches. For example, a common and effective treatment for OCD involves exposure and response prevention (ERP) to dissociate feared stimuli from compulsive and rigid behaviors and increase adaptive distress tolerance skills (Song et al., 2022). Based on prior literature, we would expect indecision and engagement in low-benefit behaviors despite negative outcomes to underlie this rigid presentation; therefore, ERP which challenges individuals with this disorder to only engage in a certain behavior once could directly target this dysfunction. ERP would not, however, adequately address the amplified decisiveness and selectivity observed in association with OCPD traits. Further, evidence suggests that the presence of comorbid OCPD interferes with ERP in those with OCD (Pinto et al., 2011), lending additional support to the supposition that the key features of the two disorders are mechanistically independent. Overall, the results of the current study suggest avenues for future interventions that may include alternative approaches in addition to those mentioned above. Subsequent research is needed to confirm the efficacy of these and other interventions in altering the mechanistic processes leading to rigidity in OCPD.

Strengths and Limitations

Notable strengths of this project include the evaluation of an under-researched population (i.e., individuals with elevated OCPD traits), the use of a sophisticated cross-species translational neuroeconomic paradigm and advanced analysis approaches, and relatively large sample size. Our findings lend additional support to the utility of neuroeconomic tasks such as Web-Surf to examine and compare abnormalities in complex decision-making processes within psychiatric populations. Importantly, this approach can be extended to address similar mechanistic questions regarding transdiagnostic behavioral symptoms (e.g., social withdrawal, irritability, attentional disturbances), with the potential to inform more precise and targeted treatments based on shared and distinct pathogenesis.

However, certain study limitations warrant considerations. First, we have framed our hypotheses using extant literature on both AN and OCD; however, to date, the Web-Surf task has only been used to examine these processes in AN (Calvin et al., 2022; Haynos, Abram, et al., 2020) and our behavioral adaptation aim has not been tested in either disorder. Therefore, we have extrapolated how we would expect individuals with OCD to perform on the Web-Surf task based on existing research utilizing related methods. It is possible that, in reality, individuals with OCD may display decision-making patterns on the Web-Surf Task that conflict with our hypotheses. Research in our group is ongoing to examine decision-making patterns among individuals with OCD on the Web-Surf Task. Therefore, these findings should be compared against our informed hypotheses in the future. In addition, certain characteristics of our sample may limit the generalizability of our findings. For example, 90% of our participants held a Bachelor's degree or higher, which may have impacted decision-making abilities and patterns. While our sample did include individuals with diverse racial, ethnic, gender, and sexual orientation identities, over half of our participants were White, cisgender, or heterosexual. Therefore, we cannot be certain that the findings would apply to groups with different demographic characteristics.

Findings should be interpreted in light of the lack of participants in our sample who fall on the most severe end of OCPD psychopathology. The range of total FFOCI-SF scores we obtained did not include the lowest or highest 15% of possible scores; thus, our results should be interpreted in the context of "subclinical" levels of OCPD traits. For this reason, some of findings may conflict with prior studies of OCPD because certain neurocognitive and decision-making processes may remain unaffected at subsyndromal presentations of OCPD (Grant & Chamberlain, 2019). Our additional exploratory analysis examining participants in the top quartile of OCPD traits was motivated by this consideration, and provided evidence that certain computational aberrations may emerge as traits become more severe. To confirm our results, individuals with clinically significant OCPD, OCD, and AN should be directly compared on these decision-making parameters. The contribution of specific personality features shared across the three diagnoses (e.g., perfectionism; Levinson et al., 2019) to decision-making patterns should also be explored to lend further clarity to the mechanistic relationship between each diagnosis. Finally, although neuroeconomic tasks afford unique opportunities to examine precise mechanisms of decision-making, it is possible that decision-making patterns captured by these tasks do not translate directly to real-world decision-making conditions that involve greater variability and uncertainty. Therefore, future research on decision-making in OCPD would benefit from a variety of methods for assessing decision-making, including those with high ecological validity.

Future Directions

Future research should seek to integrate neuroimaging with these neuroeconomic tasks among individuals with OCPD in order to characterize the functional and structural neural correlates of the abnormal decision-making observed in this population. For example, accelerated behavioral adaptation during sequential decision-making could be related to the heightened activity and functional connectivity in the precuneus noted among individuals with OCPD while at rest (Marincowitz et al., 2021). The precuneus is a brain region linked to involvement in self-referential processing and future-oriented planning, which could confer increased sensitivity to changes in internal states during subsequent decisions. Mapping decisional processes to brain activity will allow researchers to pinpoint the neurobiological origins of decision-making abnormalities through visualization of under-, over-, or differential activation of brain regions during decisional paradigms. Future research should also seek to link decision-making abnormalities with clinical outcomes in this population, including examining correlations with concomitant affective disturbances (e.g., depression, anxiety, suicidality) or impairments in functioning. This work additionally provides a foundation for examinations of cognitive and behavioral rigidity across different populations and during critical transition periods across the lifespan, during which time rigidity may become especially limiting.

Conclusion

In this study, decision-making patterns exhibited during an experiential foraging task revealed several compelling findings regarding the mechanisms underlying rigidity among individuals with elevated OCPD traits. In sum, individuals with the highest OCPD traits resembled OCD in displaying diminished sensitivity to cost. Heightened choice selectivity relative to reward was also associated with traits of OCPD, mirroring patterns seen in individuals with AN and contradictory to those expected in OCD. OCPD traits were associated with accelerated behavioral adaptation over the course of the task, diverging from the deficit we expected to observe based on prior research in OCD and AN. We additionally noted differential effects of specific trait domains on decision-making outcomes, most notably with conscientiousness predicting higher selectivity relative to both cost and reward, as well as greater behavioral adaptation. These findings bear important implications for etiological models of OCPD and future intervention research for this under-treated disorder.

References

Abram, S. V., Breton, Y.-A., Schmidt, B., Redish, A. D., & MacDonald, A. W. (2016). The Web-Surf Task: A Translational Model of Human Decision-Making. *Cognitive, Affective & Behavioral Neuroscience*, *16*(1), 37–50. https://doi.org/10.3758/s13415-015-0379-y

Abram, S. V., Hanke, M., Redish, A. D., & MacDonald, A. W. (2019). Neural signatures underlying deliberation in human foraging decisions. *Cognitive, Affective, & Behavioral Neuroscience*, *19*(6), 1492–1508. https://doi.org/10.3758/s13415-019-00733-z

Addicott, M. A., Pearson, J. M., Kaiser, N., Platt, M. L., & McClernon, F. J. (2015). Suboptimal foraging behavior: A new perspective on gambling. *Behavioral Neuroscience*, *129*(5), 656–665. https://doi.org/10.1037/bne0000082

Addicott, M. A., Pearson, J. M., Sweitzer, M. M., Barack, D. L., & Platt, M. L. (2017). A Primer on Foraging and the Explore/Exploit Trade-Off for Psychiatry Research. *Neuropsychopharmacology*, *42*(10), 1931–1939. https://doi.org/10.1038/npp.2017.108

American Psychiatric Association (Ed.). (2022). *Diagnostic and statistical manual of mental disorders: DSM-5-TR* (Fifth edition, text revision). APA Publishing.

Anderson, A. C., Youssef, G. J., Robinson, A. H., Lubman, D. I., & Verdejo-Garcia, A. (2021). Cognitive boosting interventions for impulsivity in addiction: A systematic review and meta-analysis of cognitive training, remediation and pharmacological enhancement. *Addiction (Abingdon, England)*, *116*(12), 3304–3319. https://doi.org/10.1111/add.15469

Arthurs, S. D., & Tan, J. C. H. (2017). Personality traits, early maladaptive schemas, and severity of nonsuicidal self-injury. *Psi Chi Journal of Psychological Research*, *22*(3), 181–192. https://doi.org/10.24839/2325-7342.JN22.3.181

Atroszko, P. A., Demetrovics, Z., & Griffiths, M. D. (2020). Work Addiction, Obsessive-Compulsive Personality Disorder, Burn-Out, and Global Burden of Disease: Implications from the ICD-11. *International Journal of Environmental Research and Public Health*, *17*(2), 660. https://doi.org/10.3390/ijerph17020660

Augustine, A. A., & Larsen, R. J. (2011). Affect regulation and temporal discounting: Interactions between primed, state, and trait affect: Emotion. *Emotion*, *11*(2), 403–412. https://doi.org/10.1037/a0021777

Ben-Porath, D., Duthu, F., Luo, T., Gonidakis, F., Compte, E. J., & Wisniewski, L. (2020). Dialectical behavioral therapy: An update and review of the existing treatment models adapted for adults with eating disorders. *Eating Disorders*, *28*(2), 101–121. https://doi.org/10.1080/10640266.2020.1723371

Bernardoni, F., Bernhardt, N., Pooseh, S., King, J. A., Geisler, D., Ritschel, F., Boehm, I., Seidel, M., Roessner, V., Smolka, M. N., & Ehrlich, S. (2020). Metabolic state and value-based decision-making in acute and recovered female patients with anorexia nervosa. *Journal of Psychiatry & Neuroscience : JPN*, *45*(4), 253–261. https://doi.org/10.1503/jpn.190031

Bohon, C., Weinbach, N., & Lock, J. (2020). Performance and brain activity during the Wisconsin Card Sorting Test in adolescents with obsessive-compulsive disorder and adolescents with weight-restored anorexia nervosa. *European Child & Adolescent Psychiatry*, *29*(2), 217–226. https://doi.org/10.1007/s00787-019-01350-4

Brown, M., Robinson, L., Campione, G. C., Wuensch, K., Hildebrandt, T., & Micali, N. (2017). Intolerance of Uncertainty in Eating Disorders: A Systematic Review and Meta-Analysis. *European Eating Disorders Review*, *25*(5), 329–343. https://doi.org/10.1002/erv.2523

Cain, N. M., Ansell, E. B., Simpson, H. B., & Pinto, A. (2015). Interpersonal Functioning in Obsessive-Compulsive Personality Disorder. *Journal of Personality Assessment*, *97*(1), 90–99. https://doi.org/10.1080/00223891.2014.934376

Calvin, O. L., Redish, A. D., & Haynos, A. F. (2022, November). *Hierarchical drift diffusion modeling of reaction times of individuals with anorexia nervosa on a video foraging task (WebSurf)* [Poster]. Society for Neuroscience.

Calvo, R., Lázaro, L., Castro-Fornieles, J., Font, E., Moreno, E., & Toro, J. (2009). Obsessive-compulsive personality disorder traits and personality dimensions in parents of children with obsessive-compulsive disorder. *European Psychiatry: The Journal of the Association of European Psychiatrists*, *24*(3), 201–206. https://doi.org/10.1016/j.eurpsy.2008.11.003

Carter, N. T., Guan, L., Maples, J. L., Williamson, R. L., & Miller, J. D. (2016). The downsides of extreme conscientiousness for psychological well-being: The role of obsessive compulsive tendencies. *Journal of Personality*, *84*(4), 510–522. https://doi.org/10.1111/jopy.12177

Chamberlain, S. R., Solly, J. E., Hook, R. W., Vaghi, M. M., & Robbins, T. W. (2021). Cognitive Inflexibility in OCD and Related Disorders. *Current Topics in Behavioral Neurosciences*, *49*, 125–145. https://doi.org/10.1007/7854_2020_198

Cheli, S., MacBeth, A., Popolo, R., & Dimaggio, G. (2020). The intertwined path of perfectionism and self-criticism in a client with obsessive-compulsive personality disorder. *Journal of Clinical Psychology*, *76*(11), 2055–2066. https://doi.org/10.1002/jclp.23051

Cillo, A., Bonetti, M., Burro, G., Di Serio, C., De Filippis, R., & Martoni, R. M. (2019). Neurocognitive assessment in obsessive compulsive disorder patients: Adherence to behavioral decision models. *PLoS ONE*, *14*(2), e0211856. https://doi.org/10.1371/journal.pone.0211856

Clemente, M. J., Martins Silva, A. S., Pozzolo Pedro, M. O., Paiva, H. S., de Azevedo Marques Périco, C., Torales, J., Ventriglio, A., & Castaldelli-Maia, J. M. (2022). A meta-analysis and meta-regression analysis of the global prevalence of obsessive-compulsive personality disorder. *Heliyon*, *8*(7), e09912. https://doi.org/10.1016/j.heliyon.2022.e09912

Costa, P. T., & McCrae, R. R. (1995). Domains and facets: Hierarchical personality assessment using the revised NEO personality inventory. *Journal of Personality Assessment*, *64*(1), 21–50. https://doi.org/10.1207/s15327752jpa6401_2

Craske, M. G., Meuret, A. E., Echiverri-Cohen, A., Rosenfield, D., & Ritz, T. (2023). Positive affect treatment targets reward sensitivity: A randomized controlled trial. *Journal of Consulting and Clinical Psychology*, *91*(6), 350–366. https://doi.org/10.1037/ccp0000805

Craske, M. G., Meuret, A. E., Ritz, T., Treanor, M., & Dour, H. J. (2016). Treatment for Anhedonia: A Neuroscience Driven Approach. *Depression and Anxiety*, *33*(10), 927–938. https://doi.org/10.1002/da.22490

Craske, M. G., Meuret, A. E., Ritz, T., Treanor, M., Dour, H., & Rosenfield, D. (2019). Positive affect treatment for depression and anxiety: A randomized clinical trial for a core feature of anhedonia: Journal of Consulting and Clinical Psychology. *Journal of Consulting and Clinical Psychology*, *87*(5), 457–471. https://doi.org/10.1037/ccp0000396

Cummings, J. A., Hayes, A. M., Cardaciotto, L., & Newman, C. F. (2012). The Dynamics of Self-Esteem in Cognitive Therapy for Avoidant and Obsessive-Compulsive Personality Disorders: An Adaptive Role of Self-Esteem Variability? *Cognitive Therapy and Research*, *36*(4), 272–281. https://doi.org/10.1007/s10608-011-9375-x

de Reus, R. J. M., & Emmelkamp, P. M. G. (2012). Obsessive-compulsive personality disorder: A review of current empirical findings. *Personality and Mental Health*, *6*(1), 1–21. https://doi.org/10.1002/pmh.144

DeGuzman, M., Shott, M. E., Yang, T. T., Riederer, J., & Frank, G. K. W. (2017). Association of Elevated Reward Prediction Error Response With Weight Gain in Adolescent Anorexia Nervosa. *The American Journal of Psychiatry*, *174*(6), 557–565. https://doi.org/10.1176/appi.ajp.2016.16060671

Diedrich, A., & Voderholzer, U. (2015). Obsessive–Compulsive Personality Disorder: A Current Review. *Current Psychiatry Reports*, *17*(2), 2. https://doi.org/10.1007/s11920-014-0547-8

Dimaggio, G., Carcione, A., Salvatore, G., Nicolò, G., Sisto, A., & Semerari, A. (2011). Progressively promoting metacognition in a case of obsessive-compulsive personality disorder treated with metacognitive interpersonal therapy. *Psychology & Psychotherapy: Theory, Research & Practice*, *84*(1), 70–83. https://doi.org/10.1348/147608310X527240

Dubois, M., & Hauser, T. U. (2022). Value-free random exploration is linked to impulsivity. *Nature Communications*, *13*(1), 4542. https://doi.org/10.1038/s41467-022-31918-9

Enero, C., Soler, A., Ramos, I., Cardona, S., Guillamat, R., & Valles, V. (2013). 2783 – Distress level and treatment outcome in obsessive-compulsive personality disorder (OCPD). *European Psychiatry*, *28*, 1. https://doi.org/10.1016/S0924-9338(13)77373-5

Engel, A., & Cáceda, R. (2015). Can Decision Making Research Provide a Better Understanding of Chemical and Behavioral Addictions? *Current Drug Abuse Reviews*, *8*(2), 75–85. https://doi.org/10.2174/1874473708666150916113131

Fang, L., Heisel, M. J., Duberstein, P. R., & Zhang, J. (2012). Combined effects of neuroticism and extraversion: Findings from a matched case control study of suicide in rural China. *Journal of Nervous and Mental Disease*, *200*(7), 598–602. https://doi.org/10.1097/NMD.0b013e31825bfb53

Fineberg, N. A., Day, G. A., de Koenigswarter, N., Reghunandanan, S., Kolli, S., Jefferies-Sewell, K., Hranov, G., & Laws, K. R. (2015). The neuropsychology of obsessive-compulsive personality disorder: A new analysis. *CNS Spectrums*, *20*(5), 490–499. https://doi.org/10.1017/S1092852914000662

Fossati, A., Beauchaine, T. P., Grazioli, F., Borroni, S., Carretta, I., Vecchi, C. D., Cortinovis, F., Danelli, E., & Maffei, C. (2006). Confirmatory Factor Analyses of DSM-IV Cluster C Personality Disorder Criteria. *Journal of Personality Disorders*, *20*(2), 186–203. https://doi.org/10.1521/pedi.2006.20.2.186

García-Villamisar, D., & Dattilo, J. (2015). Executive functioning in people with obsessive-compulsive personality traits: Evidence of modest impairment. *Journal of Personality Disorders*, *29*(3), 418–430. https://doi.org/10.1521/pedi_2013_27_101

Gecaite-Stonciene, J., Lochner, C., Marincowitz, C., Fineberg, N. A., & Stein, D. J. (2021). Obsessive-Compulsive (Anankastic) Personality Disorder in the ICD-11: A Scoping Review. *Frontiers in Psychiatry*, *12*, 646030. https://doi.org/10.3389/fpsyt.2021.646030

Gilbert, K., Hall, K., & Codd, R. T. (2020). Radically Open Dialectical Behavior Therapy: Social Signaling, Transdiagnostic Utility and Current Evidence. *Psychology Research and Behavior Management*, *13*, 19–28. https://doi.org/10.2147/PRBM.S201848

Glimcher, P. W., & Rustichini, A. (2004). Neuroeconomics: The Consilience of Brain and Decision. *Science*, *306*(5695), 447–452. https://doi.org/10.1126/science.1102566

Gold, J. I., & Shadlen, M. N. (2007). The neural basis of decision making. *Annual Review of Neuroscience*, *30*, 535–574. https://doi.org/10.1146/annurev.neuro.29.051605.113038

Grant, A. M., & Schwartz, B. (2011). Too Much of a Good Thing: The Challenge and Opportunity of the Inverted U. *Perspectives on Psychological Science*, *6*(1), 61–76. https://doi.org/10.1177/1745691610393523

Griffin, S. A., Suzuki, T., Lynam, D. R., Crego, C., Widiger, T. A., Miller, J. D., & Samuel, D. B. (2018). Development and Examination of the Five-Factor Obsessive-Compulsive Inventory-Short Form. *Assessment*, *25*(1), 56–68. https://doi.org/10.1177/1073191116643818

Gründler, T. O. J., Cavanagh, J. F., Figueroa, C. M., Frank, M. J., & Allen, J. J. B. (2009). Task-related dissociation in ERN amplitude as a function of obsessive-compulsive symptoms. *Neuropsychologia*, *47*(8–9), 1978–1987. https://doi.org/10.1016/j.neuropsychologia.2009.03.010

Guillaume, S., Gorwood, P., Jollant, F., Van Den Eynde, F., Courtet, P., & Richard-Devantoy, S. (2015). Impaired decision-making in symptomatic anorexia and bulimia nervosa patients: A meta-analysis. *Psychological Medicine*, *45*(16), 3377–3391. https://doi.org/10.1017/S003329171500152X

Hagan, K. E., Aimufua, I., Haynos, A. F., & Walsh, B. T. (2024). The explore/exploit trade-off: An ecologically valid and translational framework that can advance mechanistic understanding of eating disorders. *The International Journal of Eating Disorders*. https://doi.org/10.1002/eat.24173

Hagan, K. E., Christensen, K. A., & Forbush, K. T. (2020). A preliminary systematic review and meta-analysis of randomized-controlled trials of cognitive remediation therapy for anorexia nervosa. *Eating Behaviors*, *37*, 101391. https://doi.org/10.1016/j.eatbeh.2020.101391

Halmi, K. A., Tozzi, F., Thornton, L. M., Crow, S., Fichter, M. M., Kaplan, A. S., Keel, P., Klump, K. L., Lilenfeld, L. R., Mitchell, J. E., Plotnicov, K. H., Pollice, C., Rotondo, A., Strober, M., Woodside, D. B., Berrettini, W. H., Kaye, W. H., & Bulik, C. M. (2005). The relation among perfectionism, obsessive-compulsive personality disorder and obsessive-compulsive disorder in individuals with eating disorders. *International Journal of Eating Disorders*, *38*(4), 371–374. https://doi.org/10.1002/eat.20190

Hauser, T. U., Iannaccone, R., Dolan, R. J., Ball, J., Hättenschwiler, J., Drechsler, R., Rufer, M., Brandeis, D., Walitza, S., & Brem, S. (2017). Increased fronto-striatal reward prediction errors moderate decision making in obsessive-compulsive disorder. *Psychological Medicine*, *47*(7), 1246–1258. https://doi.org/10.1017/S0033291716003305

Hauser, T. U., Moutoussis, M., Iannaccone, R., Brem, S., Walitza, S., Drechsler, R., Dayan, P., & Dolan, R. J. (2017). Increased decision thresholds enhance information gathering performance in juvenile Obsessive-Compulsive Disorder (OCD). *PLoS Computational Biology*, *13*(4), e1005440. https://doi.org/10.1371/journal.pcbi.1005440

Hauser, T. U., Moutoussis, M., NSPN Consortium, Dayan, P., & Dolan, R. J. (2017). Increased decision thresholds trigger extended information gathering across the compulsivity spectrum. *Translational Psychiatry*, *7*(12), 1296. https://doi.org/10.1038/s41398-017-0040-3

Haynos, A. F., Abram, S. V., MacDonald, A. W., Redish, A. D., & Crow, S. J. (2020, October). *Novel decision-making mechanisms of anorexia nervosa emerging from a computationally-informed translational approach*. Eating Disorder Research Society.

Haynos, A. F., Anderson, L. M., Askew, A. J., Craske, M. G., & Peterson, C. B. (2021). Adapting a neuroscience-informed intervention to alter reward mechanisms of anorexia nervosa: A novel direction for future research. *Journal of Eating Disorders*, *9*(1), 63. https://doi.org/10.1186/s40337-021-00417-5

Haynos, A. F., Anderson, L. M., Askew, A. J., Liu, C., Venables, K., Craske, M. G., & Peterson, C. B. (2023). A randomized, controlled pilot study of positive affect treatment adapted for anorexia nervosa. *The International Journal of Eating Disorders*. https://doi.org/10.1002/eat.24071

Haynos, A. F., Lavender, J. M., Nelson, J., Crow, S. J., & Peterson, C. B. (2020). Moving towards Specificity: A Systematic Review of Cue Features Associated with Reward and Punishment in Anorexia Nervosa. *Clinical Psychology Review*, *79*, 101872. https://doi.org/10.1016/j.cpr.2020.101872

Haynos, A. F., Widge, A. S., Anderson, L. M., & Redish, A. D. (2022). Beyond Description and Deficits: How Computational Psychiatry Can Enhance an Understanding of Decision-Making in Anorexia Nervosa. *Current Psychiatry Reports*, *24*(1), 77–87. https://doi.org/10.1007/s11920-022-01320-9

Huynh, T., Alstatt, K., Abram, S. V., & Schmitzer-Torbert, N. (2021). Vicarious Trial-and-Error Is Enhanced During Deliberation in Human Virtual Navigation in a Translational Foraging Task. *Frontiers in Behavioral Neuroscience*, *15*, 586159. https://doi.org/10.3389/fnbeh.2021.586159

Ionescu, T. (2012). Exploring the nature of cognitive flexibility. *New Ideas in Psychology*, *30*, 190–200. https://doi.org/10.1016/j.newideapsych.2011.11.001

Jacoby, R. J., Szkutak, A., Shin, J., Lerner, J., & Wilhelm, S. (2023). Feeling uncertain despite knowing the risk: Patients with OCD (but not controls) experience known and unknown probabilistic decisions as similarly distressing and uncertain. *Journal of Obsessive-Compulsive and Related Disorders*, *39*, 100842. https://doi.org/10.1016/j.jocrd.2023.100842

Jennings, A. F. (2023). *Emotional overcontrol as a predictor of treatment outcome in obsessive-compulsive disorder* (2023-01890-059; Issues 2-B). ProQuest Information & Learning.

Kalenscher, T., & van Wingerden, M. (2011). Why We Should Use Animals to Study Economic Decision Making – A Perspective. *Frontiers in Neuroscience*, *5*, 82. https://doi.org/10.3389/fnins.2011.00082

Kanen, J. W., Ersche, K. D., Fineberg, N. A., Robbins, T. W., & Cardinal, R. N. (2019). Computational modelling reveals contrasting effects on reinforcement learning and cognitive flexibility in stimulant use disorder and obsessive-compulsive disorder: Remediating effects of dopaminergic D2/3 receptor agents. *Psychopharmacology*, *236*(8), 2337–2358. https://doi.org/10.1007/s00213-019-05325-w

Keegan, E., Tchanturia, K., & Wade, T. D. (2021). Central coherence and set-shifting between nonunderweight eating disorders and anorexia nervosa: A systematic review and meta-analysis. *International Journal of Eating Disorders*, *54*(3), 229–243. https://doi.org/10.1002/eat.23430

King, J. A., Geisler, D., Bernardoni, F., Ritschel, F., Böhm, I., Seidel, M., Mennigen, E., Ripke, S., Smolka, M. N., Roessner, V., & Ehrlich, S. (2016). Altered Neural Efficiency of Decision Making During Temporal Reward Discounting in Anorexia Nervosa. *Journal of the American Academy of Child and Adolescent Psychiatry*, *55*(11), 972–979. https://doi.org/10.1016/j.jaac.2016.08.005

Koob, G. F., & Volkow, N. D. (2016). Neurobiology of addiction: A neurocircuitry analysis. *The Lancet. Psychiatry*, *3*(8), 760–773. https://doi.org/10.1016/S2215-0366(16)00104-8

Kramer, U., Eubanks, C. F., Bertsch, K., Herpertz, S. C., McMain, S., Mehlum, L., Renneberg, B., & Zimmermann, J. (2022). Future Challenges in Psychotherapy Research for Personality Disorders. *Current Psychiatry Reports*, *24*(11), 613–622. https://doi.org/10.1007/s11920-022-01379-4

Lempert, K. M., Steinglass, J. E., Pinto, A., Kable, J. W., & Simpson, H. B. (2019). Can delay discounting deliver on the promise of RDoC? *Psychological Medicine*, *49*(2), 190–199. https://doi.org/10.1017/S0033291718001770

Levinson, C. A., Zerwas, S. C., Brosof, L. C., Thornton, L. M., Strober, M., Pivarunas, B., Crowley, J. J., Yilmaz, Z., Berrettini, W. H., Brandt, H., Crawford, S., Fichter, M. M., Halmi, K. A., Johnson, C., Kaplan, A. S., La Via, M., Mitchell, J., Rotondo, A., Woodside, D. B., … Bulik, C. M. (2019). Associations between Dimensions of Anorexia Nervosa and Obsessive-Compulsive Disorder: An Examination of Personality and Psychological Factors in Patients with Anorexia Nervosa. *European Eating Disorders*

Review : The Journal of the Eating Disorders Association, *27*(2), 161–172. https://doi.org/10.1002/erv.2635

Luo, Y., Chen, L., Li, H., Dong, Y., Zhou, X., Qiu, L., Zhang, L., Gao, Y., Zhu, C., Yu, F., & Wang, K. (2020). Do Individuals With Obsessive-Compulsive Disorder and Obsessive-Compulsive Personality Disorder Share Similar Neural Mechanisms of Decision-Making Under Ambiguous Circumstances? *Frontiers in Human Neuroscience*, *14*, 585086. https://doi.org/10.3389/fnhum.2020.585086

Luoma, J. B., Hayes, S. C., & Walser, R. D. (2017). *Learning ACT: An Acceptance and Commitment Therapy Skills Training Manual for Therapists*. Context Press. http://ebookcentral.proquest.com/lib/vcu/detail.action?docID=4819719

Lynch, T. R., & Cheavens, J. S. (2008). Dialectical behavior therapy for comorbid personality disorders. *Journal of Clinical Psychology*, *64*(2), 154–167. https://doi.org/10.1002/jclp.20449

Lynch, T. R., Hempel, R. J., & Dunkley, C. (2015). Radically Open-Dialectical Behavior Therapy for Disorders of Over-Control: Signaling Matters. *American Journal of Psychotherapy*, *69*(2), 141–162. https://doi.org/10.1176/appi.psychotherapy.2015.69.2.141

Mandali, A., Weidacker, K., Kim, S.-G., & Voon, V. (2019). The ease and sureness of a decision: Evidence accumulation of conflict and uncertainty. *Brain: A Journal of Neurology*, *142*(5), 1471–1482. https://doi.org/10.1093/brain/awz013

Manning, J., Hedden, T., Wickens, N., Whitfield-Gabrieli, S., Prelec, D., & Gabrieli, J. D. E. (2014). Personality influences temporal discounting preferences: Behavioral and brain evidence. *NeuroImage*, *98*, 42–49. https://doi.org/10.1016/j.neuroimage.2014.04.066

Marincowitz, C., Lochner, C., & Stein, D. J. (2021). The neurobiology of obsessive-compulsive personality disorder: A systematic review. *CNS Spectrums*, 1–12. https://doi.org/10.1017/S1092852921000754

Marzuki, A. A., Tomić, I., Ip, S. H. Y., Gottwald, J., Kanen, J. W., Kaser, M., Sule, A., Conway-Morris, A., Sahakian, B. J., & Robbins, T. W. (2021). Association of Environmental Uncertainty With Altered Decision-making and Learning Mechanisms in Youths With Obsessive-Compulsive Disorder. *JAMA Network Open*, *4*(11), e2136195. https://doi.org/10.1001/jamanetworkopen.2021.36195

McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and its Applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McGlashan, T. H., Grilo, C. M., Sanislow, C. A., Ralevski, E., Morey, L. C., Gunderson, J. G., Skodol, A. E., Shea, M. T., Zanarini, M. C., Bender, D., Stout, R. L., Yen, S., & Pagano, M. (2005). Two-Year Prevalence and Stability of Individual DSM-IV Criteria for Schizotypal, Borderline, Avoidant, and Obsessive-Compulsive Personality Disorders: Toward a Hybrid Model of Axis II Disorders. *American Journal of Psychiatry*, *162*(5), 883–889. https://doi.org/10.1176/appi.ajp.162.5.883

Ng, R. M. K. (2005). Cognitive Therapy for Obsessive-compulsive Personality Disorder—A Pilot Study in Hong Kong Chinese Patients. *Hong Kong Journal of Psychiatry*, *15*, 50–53.

Nielen, M. M., Den Boer, J. A., & Smid, H. G. O. M. (2009). Patients with obsessive–compulsive disorder are impaired in associative learning based on external feedback. *Psychological Medicine*, *39*(9), 1519–1526. https://doi.org/10.1017/S0033291709005297

O’Brien, J. L., Jacob, M. L., & King, M. (2019). Preliminary evidence of biased attentional mechanisms and reward processing in adults with obsessive-compulsive disorder. *Bulletin of the Menninger Clinic*, *83*(2), 128–151. https://doi.org/10.1521/bumc.2019.83.2.128

Paast, N., Khosravi, Z., Memari, A. H., Shayestehfar, M., & Arbabi, M. (2016). Comparison of cognitive flexibility and planning ability in patients with obsessive compulsive disorder, patients with obsessive compulsive personality disorder, and healthy controls. *Shanghai Archives of Psychiatry*, *28*(1), 28–34. https://doi.org/10.11919/j.issn.1002-0829.215124

Paret, C., Jennen-Steinmetz, C., & Schmahl, C. (2017). Disadvantageous decision-making in borderline personality disorder: Partial support from a meta-analytic review. *Neuroscience and Biobehavioral Reviews*, *72*, 301–309. https://doi.org/10.1016/j.neubiorev.2016.11.019

Piedmont, R. L., Sherman, M. F., Sherman, N. C., Dy-Liacco, G. S., & Williams, J. E. G. (2009). Using the five-factor model to identify a new personality disorder domain: The case for experiential permeability. *Journal of Personality and Social Psychology*, *96*(6), 1245–1258. https://doi.org/10.1037/a0015368

Pinto, A., Liebowitz, M. R., Foa, E. B., & Simpson, H. B. (2011). Obsessive compulsive personality disorder as a predictor of exposure and ritual prevention outcome for obsessive compulsive disorder. *Behaviour Research and Therapy*, *49*(8), 453–458. https://doi.org/10.1016/j.brat.2011.04.004

Pinto, A., Steinglass, J. E., Greene, A. L., Weber, E. U., & Simpson, H. B. (2014). Capacity to delay reward differentiates obsessive-compulsive disorder and obsessive-compulsive personality disorder. *Biological Psychiatry*, *75*(8), 653–659. https://doi.org/10.1016/j.biopsych.2013.09.007

Pinto, A., Teller, J., & Wheaton, M. G. (2022). Obsessive-Compulsive Personality Disorder: A Review of Symptomatology, Impact on Functioning, and Treatment. *FOCUS*, *20*(4), 389–396. https://doi.org/10.1176/appi.focus.20220058

Platt, J. R. (1964). Strong Inference: Certain systematic methods of scientific thinking may produce much more rapid progress than others. *Science (New York, N.Y.)*, *146*(3642), 347–353. https://doi.org/10.1126/science.146.3642.347

Popolo, R., MacBeth, A., Lazzerini, L., Brunello, S., Venturelli, G., Rebecchi, D., Morales, M. F., & Dimaggio, G. (2022). Metacognitive interpersonal therapy in group versus TAU + waiting list for young adults with personality disorders: Randomized clinical trial. *Personality Disorders: Theory, Research, and Treatment*, *13*(6), 619–628. https://doi.org/10.1037/per0000497

Pushkarskaya, H., Tolin, D., Ruderman, L., Henick, D., Kelly, J. M., Pittenger, C., & Levy, I. (2017). Value-based decision making under uncertainty in hoarding and obsessive-compulsive disorders. *Psychiatry Research*, *258*, 305–315. https://doi.org/10.1016/j.psychres.2017.08.058

Quilty, L. C., Mainland, B. J., McBride, C., & Bagby, R. M. (2013). Interpersonal problems and impacts: Further evidence for the role of interpersonal functioning in treatment outcome in major depressive disorder. *Journal of Affective Disorders*, *150*(2), 393–400. https://doi.org/10.1016/j.jad.2013.04.030

Raghunathan, T., Lepkowski, J., Hoewyk, J., & Solenberger, P. (2000). A Multivariate Technique for Multiply Imputing Missing Values Using a Sequence of Regression Models. *Survey Methodology*, *27*.

Redish, A. D. (2016). Vicarious trial and error. *Nature Reviews. Neuroscience*, *17*(3), 147–159. https://doi.org/10.1038/nrn.2015.30

Redish, A. D., Jensen, S., & Johnson, A. (2008). A unified framework for addiction: Vulnerabilities in the decision process. *Behavioral and Brain Sciences*, *31*(4), 415–437. https://doi.org/10.1017/S0140525X0800472X

Redish, A. D., Kepecs, A., Anderson, L. M., Calvin, O. L., Grissom, N. M., Haynos, A. F., Heilbronner, S. R., Herman, A. B., Jacob, S., Ma, S., Vilares, I., Vinogradov, S., Walters, C. J., Widge, A. S., Zick, J. L., & Zilverstand, A. (2021). Computational validity: Using computation to translate behaviours across species. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1844), 20200525. https://doi.org/10.1098/rstb.2020.0525

Riddle, M. A., Maher, B. S., Wang, Y., Grados, M., Bienvenu, O. J., Goes, F. S., Cullen, B., Murphy, D. L., Rauch, S. L., Greenberg, B. D., Knowles, J. A., McCracken, J. T., Pinto, A., Piacentini, J., Pauls, D. L., Rasmussen, S. A., Shugart, Y. Y., Nestadt, G., & Samuels, J. (2016). Obsessive–compulsive personality disorder: Evidence for two dimensions. *Depression and Anxiety*, *33*(2), 128–135. https://doi.org/10.1002/da.22452

Robson, S. E., Repetto, L., Gountouna, V.-E., & Nicodemus, K. K. (2020). A review of neuroeconomic gameplay in psychiatric disorders. *Molecular Psychiatry*, *25*(1), 67–81. https://doi.org/10.1038/s41380-019-0405-5

Rotge, J.-Y., Langbour, N., Dilharreguy, B., Bordessoulles, M., Guehl, D., Bioulac, B., Martin-Guehl, C., Jaafari, N., Aouizerate, B., Allard, M., & Burbaud, P. (2015). Contextual and behavioral influences on uncertainty in obsessive-compulsive disorder. *Cortex*, *62*, 1–10. https://doi.org/10.1016/j.cortex.2012.12.010

Rothenberg, A. (1986). Eating disorder as a modern obsessive-compulsive syndrome. *Psychiatry*, *49*(1), 45–53. https://doi.org/10.1080/00332747.1986.11024306

Sachdev, P. S., & Malhi, G. S. (2005). Obsessive–Compulsive Behaviour: A Disorder of Decision-Making. *Australian & New Zealand Journal of Psychiatry*, *39*(9), 757–763. https://doi.org/10.1080/j.1440-1614.2005.01680.x

Samuel, D. B., Riddell, A. D. B., Lynam, D. R., Miller, J. D., & Widiger, T. A. (2012). A Five-Factor Measure of Obsessive–Compulsive Personality Traits. *Journal of Personality Assessment*, *94*(5), 456–465. https://doi.org/10.1080/00223891.2012.677885

Schmidt, B., Duin, A. A., & Redish, A. D. (2019). Disrupting the medial prefrontal cortex alters hippocampal sequences during deliberative decision making. *Journal of Neurophysiology*, *121*(6), 1981–2000. https://doi.org/10.1152/jn.00793.2018

Scholl, J., & Klein-Flügge, M. (2018). Understanding psychiatric disorder by capturing ecologically relevant features of learning and decision-making. *Behavioural Brain Research*, *355*, 56–75. https://doi.org/10.1016/j.bbr.2017.09.050

Schultz, W., Dayan, P., & Montague, P. R. (1997). A neural substrate of prediction and reward. *Science (New York, N.Y.)*, *275*(5306), 1593–1599. https://doi.org/10.1126/science.275.5306.1593

Serpell, L., Livingstone, A., Neiderman, M., & Lask, B. (2002). Anorexia nervosa: Obsessive-compulsive disorder, obsessive-compulsive personality disorder, or neither? *Clinical Psychology Review*, *22*(5), 647–669. https://doi.org/10.1016/s0272-7358(01)00112-x

Shafran, R., Egan, S. J., & Wade, T. D. (2023). Coming of age: A reflection of the first 21 years of cognitive behaviour therapy for perfectionism. *Behaviour Research and Therapy*, *161*, 104258. https://doi.org/10.1016/j.brat.2023.104258

Sheehan, D. V., Lecrubier, Y., Sheehan, K. H., Amorim, P., Janavs, J., Weiller, E., Hergueta, T., Baker, R., & Dunbar, G. C. (1998). The Mini-International Neuropsychiatric Interview (M.I.N.I.): The development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. *The Journal of Clinical Psychiatry*, *59 Suppl 20*, 22-33;quiz 34-57.

Sloan, E., Hall, K., Moulding, R., Bryce, S., Mildred, H., & Staiger, P. K. (2017). Emotion regulation as a transdiagnostic treatment construct across anxiety, depression, substance, eating and borderline personality disorders: A systematic review. *Clinical Psychology Review*, *57*, 141–163. https://doi.org/10.1016/j.cpr.2017.09.002

Smith, R., Shepard, C., Wiltgen, A., Rufino, K., & Fowler, J. C. (2017). Treatment outcomes for inpatients with obsessive-compulsive personality disorder: An open comparison trial. *Journal of Affective Disorders*, *209*, 273–278. https://doi.org/10.1016/j.jad.2016.12.002

Soeteman, D. I., Hakkaart-van Roijen, L., Verheul, R., & Busschbach, J. J. V. (2008). The economic burden of personality disorders in mental health care. *The Journal of Clinical Psychiatry*, *69*(2), 259–265. https://doi.org/10.4088/jcp.v69n0212

Song, Y., Li, D., Zhang, S., Jin, Z., Zhen, Y., Su, Y., Zhang, M., Lu, L., Xue, X., Luo, J., Liang, M., & Li, X. (2022). The effect of exposure and response prevention therapy on obsessive-compulsive disorder: A systematic review and meta-analysis. *Psychiatry Research*, *317*, 114861. https://doi.org/10.1016/j.psychres.2022.114861

Speers, L. J., & Bilkey, D. K. (2023). Maladaptive explore/exploit trade-offs in schizophrenia. *Trends in Neurosciences*, *46*(5), 341–354. https://doi.org/10.1016/j.tins.2023.02.001

Starcevic, V., & Brakoulias, V. (2014). New diagnostic perspectives on obsessive-compulsive personality disorder and its links with other conditions. *Current Opinion in Psychiatry*, *27*(1), 62–67. https://doi.org/10.1097/YCO.0000000000000030

Steiner, A. P., & Redish, A. D. (2014). Behavioral and neurophysiological correlates of regret in rat decision-making on a neuroeconomic task. *Nature Neuroscience*, *17*(7), 995–1002. https://doi.org/10.1038/nn.3740

Steinglass, J. E., Lempert, K. M., Choo, T.-H., Kimeldorf, M. B., Wall, M., Walsh, B. T., Fyer, A. J., Schneier, F. R., & Simpson, H. B. (2017). Temporal discounting across three psychiatric disorders: Anorexia nervosa, obsessive compulsive disorder, and social anxiety disorder. *Depression and Anxiety*, *34*(5), 463–470. https://doi.org/10.1002/da.22586

Stephens, D. W. (2008). Decision ecology: Foraging and the ecology of animal decision making. *Cognitive, Affective, & Behavioral Neuroscience*, *8*(4), 475–484. https://doi.org/10.3758/CABN.8.4.475

Stotts, A. L., Vujanovic, A., Heads, A., Suchting, R., Green, C. E., & Schmitz, J. M. (2015). The role of avoidance and inflexibility in characterizing response to contingency management for cocaine use disorders: A secondary profile analysis. *Psychology of Addictive Behaviors*, *29*(2), 408–413. https://doi.org/10.1037/adb0000011

Strauss, J. L., Hayes, A. M., Johnson, S. L., Newman, C. F., Brown, G. K., Barber, J. P., Laurenceau, J.-P., & Beck, A. T. (2006). Early alliance, alliance ruptures, and symptom change in a nonrandomized trial of cognitive therapy for avoidant and obsessive-compulsive personality disorders. *Journal of Consulting and Clinical Psychology*, *74*(2), 337–345. https://doi.org/10.1037/0022-006X.74.2.337

Strober, M., Freeman, R., Lampert, C., & Diamond, J. (2007). The association of anxiety disorders and obsessive compulsive personality disorder with anorexia nervosa: Evidence from a family study with discussion of nosological and neurodevelopmental implications. *The International Journal of Eating Disorders*, *40 Suppl*, S46-51. https://doi.org/10.1002/eat.20429

Suzuki, T., Griffin, S. A., & Samuel, D. B. (2017). Capturing the DSM-5 Alternative Personality Disorder Model Traits in the Five-Factor Model's Nomological Net. *Journal of Personality*, *85*(2), 220–231. https://doi.org/10.1111/jopy.12235

Sweis, B. M., Abram, S. V., Schmidt, B. J., Seeland, K. D., MacDonald, A. W., Thomas, M. J., & Redish, A. D. (2018). Sensitivity to "sunk costs" in mice, rats, and humans. *Science (New York, N.Y.)*, *361*(6398), 178–181. https://doi.org/10.1126/science.aar8644

Sweis, B. M., Thomas, M. J., & Redish, A. D. (2018). Mice learn to avoid regret. *PLoS Biology*, *16*(6), e2005853. https://doi.org/10.1371/journal.pbio.2005853

Taylor, S., Asmundson, G. J. G., & Jang, K. L. (2011). Etiology of obsessive-compulsive symptoms and obsessive-compulsive personality traits: Common genes, mostly different environments: Depression & Anxiety (1091-4269). *Depression & Anxiety (1091-4269)*, *28*(10), 863–869. https://doi.org/10.1002/da.20859

Treadway, M. T., & Salamone, J. D. (2022). Vigor, Effort-Related Aspects of Motivation and Anhedonia. *Current Topics in Behavioral Neurosciences*, *58*, 325–353. https://doi.org/10.1007/7854_2022_355

Treadway, M. T., & Zald, D. H. (2013). Parsing Anhedonia: Translational Models of Reward-Processing Deficits in Psychopathology. *Current Directions in Psychological Science*, *22*(3), 244–249. https://doi.org/10.1177/0963721412474460

Uddin, L. Q. (2021). Cognitive and behavioural flexibility: Neural mechanisms and clinical considerations. *Nature Reviews. Neuroscience*, *22*(3), 167–179. https://doi.org/10.1038/s41583-021-00428-w

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Van den Driessche, C., Chevrier, F., Cleeremans, A., & Sackur, J. (2019). Lower Attentional Skills predict increased exploratory foraging patterns. *Scientific Reports*, *9*, 10948. https://doi.org/10.1038/s41598-019-46761-0

Verharen, J. P. H., Adan, R. A. H., & Vanderschuren, L. J. M. J. (2020). How Reward and Aversion Shape Motivation and Decision Making: A Computational Account. *The Neuroscientist*, *26*(1), 87–99. https://doi.org/10.1177/1073858419834517

Verheul, R., & Widiger, T. A. (2004). A meta-analysis of the prevalence and usage of the personality disorder not otherwise specified (PDNOS) diagnosis. *Journal of Personality Disorders*, *18*(4), 309–319. https://doi.org/10.1521/pedi.18.4.309.40350

Villemarette-Pittman, N. R., Stanford, M. S., Greve, K. W., Houston, R. J., & Mathias, C. W. (2004). Obsessive—Compulsive Personality Disorder and Behavioral Disinhibition. *The Journal of Psychology*, *138*(1), 5–22. https://doi.org/10.3200/JRLP.138.1.5-22

Widiger, T. A., & Trull, T. J. (2007). Plate tectonics in the classification of personality disorder: Shifting to a dimensional model. *American Psychologist*, *62*(2), 71–83. https://doi.org/10.1037/0003-066X.62.2.71

World Health Organization. (2019). *International Statistical Classification of Diseases and Related Health Problems* (11th ed.). https://icd.who.int/

Young, S., Rhodes, P., Touyz, S., & Hay, P. (2013). The relationship between obsessive-compulsive personality disorder traits, obsessive-compulsive disorder and excessive exercise in patients with anorexia nervosa: A systematic review. *Journal of Eating Disorders*, *1*, 16. https://doi.org/10.1186/2050-2974-1-16

Zvolensky, M. J., Farris, S. G., Schmidt, N. B., & Smits, J. A. J. (2014). The role of smoking inflexibility/avoidance in the relation between anxiety sensitivity and tobacco use and beliefs among treatment-seeking smokers. *Experimental and Clinical Psychopharmacology*, *22*(3), 229–237. https://doi.org/10.1037/a0035306

Table 1

Sample Characteristics.

Variable	**Total *N*=83**
	Mean (SD) [Range]
Age (years)	33.18 (9.07) [19-61]
Gender	*N* (%)
Cisgender woman	52 (62.7)
Cisgender man	21 (25.3)
Transmasculine or transgender man	2 (2.4)
Transfeminine or transgender woman	0 (0)
Genderqueer	1 (1.2)
Agender	0 (0)
Non-binary	4 (4.8)
Gender non-conforming	1 (1.2)
Androgynous	1 (1.2)
Not sure/questioning	0 (0.0)
Not listed	0 (0)
Sexual Orientation	
Heterosexual	61 (73.5)
Asexual	1 (1.2)
Bisexual	11 (13.3)
Gay	7 (8.4)
Lesbian	3 (3.6)
Pansexual	4 (4.8)
Queer	7 (8.4)
Questioning	1 (1.2)
Another sexual orientation	0
I prefer not to answer	0
Race	
White/Caucasian (non-Hispanic/Latinx)	55 (66.3)
Black/African American	4 (4.8)
Asian/Asian American/Pacific Islander	17 (20.5)
Hispanic/Latinx or of Spanish origin	6 (7.2)
American Indian/Native American	1 (1.2)
Biracial/Multiracial	4 (4.8)
Not listed	0 (0)
Marital Status	
Single, never married	32 (38.6)
Married (first marriage)	28 (33.7)
Divorced or widowed, presently married	2 (2.4)

Monogamous relationship, living w/ partner	8 (9.6)
Monogamous relationship, not living w/ partner	11 (13.3)
Polyamorous relationship, living w/ partner(s)	1 (1.2)
Polyamorous relationship, not living w/ partner(s)	0
Divorced and not presently married	3 (3.6)
Widowed and not presently married	0
Education	
1+ years of college, no degree	8 (9.6)
Associate degree	2 (2.4)
Bachelor's degree	32 (38.6)
Master's degree	31 (37.3)
Professional degree	3 (3.6)
Doctorate degree	7 (8.4)
Household income per year	
Less than $20,000	2 (2.4)
$20,000 – $34,999	6 (7.2)
$35,000 – $49,999	13 (15.7)
$50,000 – $74,999	20 (24.1)
$75,000 – $99,999	13 (15.7)
$100,000 – $149,999	13 (15.7)
$150,000 – $199,999	9 (10.8)
More than $200,000	7 (8.1)
Employment Status	
Wage earner, full-time	74 (89.2)
Wage earner, part-time	8 (9.6)
Student, full-time	5 (6.0)
Student, part-time	5 (6.0)
Stay-at-home parent or homemaker	0
Unemployed	0

Table 2.

Obsessive-Compulsive Personality Disorder Traits Assessed by the Five-Factor Obsessive-Compulsive Inventory – Short Form.

Trait Domain/Trait Facet	Definition
Neuroticism	
Excessive Worry	Rumination; anxiety.
Extraversion	
Detached Coldness	Lack of warmth, intimacy, engagement with others.
Risk Aversion	Preference to avoid risk or unpredictability.
Openness	
Constricted	Lack of empathy; restricted range of emotions.
Inflexibility	Rigidity; reliance on routine.
Dogmatism	Moral rigidity; authoritarianism.
Conscientiousness	
Perfectionism	Need for work to be flawless.
Fastidiousness	Nature of being detail-oriented, planful, and organized.
Punctiliousness	Excessive rule-following.
Workaholism	Addiction to work.
Doggedness	Self-discipline and determination.
Ruminative Deliberation	Over-contemplation when making decisions.

Note. Adapted from Griffin et al., 2018.

Table 3.

Descriptive Statistics and Pearson Correlations for Primary Measures and Covariates.

Variable	M (SD)	Min	Max	2	3	4	5	6	7	8	9	10	11
1. Number of trials completed	94.34 (39.45)	6	248	-.13	.02	-.14	-.25*	-.06	.11	.37*	-.25*	.74*	-.69*
2. Total OCPD score	152.30 (26.62)	86	206	-	.49*	.59*	.75*	.90*	.17	-.05	-.06	-.06	.05
3. Neuroticism score	14.75 (3.81)	5	20		-	.21	.18	.39*	.21	.08	.12	-.01	-.04
4. Extraversion score	22.13 (5.41)	10	33			-	.67*	.25*	-.13	-.10	.04	.00	.03
5. Openness score	31.80 (7.40)	16	45				-	.46*	-.01	-.17	-.02	-.11	.14
6. Conscientiousness score	83.67 (17.69)	40	120					-	.26*	.00	-.12	-.05	.01
7. Enjoyment rating[1]	3.67 (0.73)	1.48	5						-	-.03	-.01	.03	-.00
8. Choice reaction time (proportion)	.15 (.05)	.06	.41							-	.15	.46	.-.75
9. Rating reaction time (proportion)	.08 (.03)	.01	.15								-	-.44*	-.02
10. Transit reaction time (proportion)	.17 (.08)	.08	.59									-	-.78*
11. Delay reaction time (proportion)	.61 (.09)	.21	.77										-

Note. OCPD = Obsessive-compulsive personality disorder, M = mean, SD = standard deviation. *significant at $p < .05$.

[1]Enjoyment rating averaged across all trials for each participant.

Table 4.

Choice Decisiveness Predicted by Total OCPD Traits.

Task Element	B	SE B	*t/z*	p
Proportion of time spent choosing				
(Intercept)	-2.01	0.29	-6.96	<.001*
OCPD traits	<0.0001	0.001	0.02	.982
Number of trials completed	0.004	0.001	3.78	<.001*
Data completeness	-0.11	0.11	-1.021	.310
Proportion of time spent waiting for delays				
(Intercept)	0.38	0.75	0.50	.615
OCPD traits	-0.001	0.004	-0.14	.893
Number of trials completed	-0.004	0.003	-1.15	.252
Data completeness	0.05	0.296	0.17	.866
Proportion of time spent rating videos				
(Intercept)	-1.94	0.26	-7.59	<.001*
OCPD traits	-0.001	0.001	-0.62	.536
Number of trials completed	-0.003	0.001	-2.88	.005*
Data completeness	-0.06	0.10	-0.65	.518
Proportion of time spent traveling				
(Intercept)	-1.05	0.83	-1.27	.203
OCPD traits	-0.001	0.005	-0.25	.803
Number of trials completed	0.009	0.003	3.28	.001*
Data completeness	0.02	0.36	0.06	.955

*significant at $p < .05$ following Benjamini-Hochberg correction for multiple comparisons.

Table 4a.

Choice Decisiveness Predicted by OCPD Traits Measured Categorically.

Task Element	B	SE B	*t/z*	p
Proportion of time spent choosing				
(Intercept)	-2.28	0.02	-140.64	<.001*
OCPD traits (0=lower 75%, 1=top 25%)	-0.12	0.01	-11.45	<.001*
Number of trials completed	0.004	<0.001	49.11	<.001*
Data completeness	0.15	0.02	10.15	<.001*
Proportion of time spent waiting for delays				
(Intercept)	0.42	0.04	10.07	<.001*
OCPD traits (0=lower 75%, 1=top 25%)	0.01	0.03	0.26	.792
Number of trials completed	-0.005	<0.001	-16.11	<.001*
Data completeness	0.07	0.04	1.98	.047
Proportion of time spent rating videos				
(Intercept)	-2.46	0.02	-164.07	<.001*
OCPD traits (0=lower 75%, 1=top 25%)	0.004	0.009	0.45	.650
Number of trials completed	-0.003	<0.001	-36.82	<.001*
Data completeness	0.43	0.01	31.34	<.001*
Proportion of time spent traveling				
(Intercept)	-0.79	0.04	-19.08	<.001*
OCPD traits (0=lower 75%, 1=top 25%)	-0.20	0.03	-6.41	<.001*
Number of trials completed	0.009	<0.001	35.69	<.001*
Data completeness	-0.43	0.04	-11.24	<.001*

*significant at $p < .05$ following Benjamini-Hochberg correction for multiple comparisons.

Table 4b.

Choice Decisiveness Predicted by OCPD Trait Domains.

Task Element	B	SE B	*t/z*	p
Proportion of time spent choosing				
Neuroticism (higher = greater neuroticism)				
(Intercept)	-2.15	0.21	-10.36	<.001*
Neuroticism traits	0.01	0.01	0.97	.333
Number of trials completed	0.004	0.001	3.81	<.001*
Data completeness	-0.14	0.12	-1.21	.229
Extraversion (higher = less extraversion)				
(Intercept)	-1.88	0.25	-7.63	<.001*
Extraversion traits	-0.005	0.01	-0.60	.548
Number of trials completed	0.004	0.001	3.70	<.001*
Data completeness	-0.12	0.11	-1.09	.280
Openness (higher = less openness)				
(Intercept)	-1.88	0.25	-7.63	<.001*
Openness traits	-0.001	0.01	-0.91	.363
Number of trials completed	0.004	0.001	3.52	<.001*
Data completeness	-0.12	0.11	-1.04	.301
Conscientiousness (higher = greater consciousness)				
(Intercept)	-2.08	0.24	-8.56	<.001*
Conscientiousness traits	0.001	0.002	0.39	.699
Number of trials completed	0.003	0.001	3.823	<.001*
Data completeness	-0.12	0.11	-1.08	.286
Proportion of time spent waiting for delays				
Neuroticism (higher = greater neuroticism)				
(Intercept)	0.32	0.53	0.60	.549
Neuroticism traits	-0.002	0.03	-0.07	.945
Number of trials completed	-0.003	0.003	-1.14	.254
Data completeness	0.05	0.30	-0.16	.870
Extraversion (higher = less extraversion)				
(Intercept)	0.37	0.65	0.57	.566
Extraversion traits	-0.003	0.02	-0.15	.879
Number of trials completed	-0.004	0.003	-1.15	.251
Data completeness	0.04	0.30	0.13	.894
Openness (higher = less openness)				
(Intercept)	0.35	0.68	0.51	.609

Openness traits	-0.002	0.02	-0.10	.920
Number of trials completed	-0.004	0.003	-1.12	.263
Data completeness	0.05	0.29	0.15	.878
Conscientiousness (higher = greater consciousness)				
(Intercept)	0.34	0.62	0.55	.586
Conscientiousness traits	-0.001	0.006	-0.10	.921
Number of trials completed	-0.003	0.003	-1.15	.252
Data completeness	0.05	0.30	0.17	.867
Proportion of time spent rating videos				
Neuroticism (higher = greater neuroticism)				
(Intercept)	-2.23	0.18	-12.36	<.001*
Neuroticism traits	0.01	0.01	1.13	.260
Number of trials completed	-0.003	0.001	-2.86	.005*
Data completeness	-0.09	0.10	-0.95	.347
Extraversion (higher = less extraversion)				
(Intercept)	-2.06	0.22	-9.38	<.001*
Extraversion traits	-0.001	0.007	-0.10	.922
Number of trials completed	-0.002	0.001	-2.80	.006*
Data completeness	-0.07	0.10	-0.73	.465
Openness (higher = less openness)				
(Intercept)	-1.95	0.23	-8.47	<.001*
Openness traits	-0.004	0.005	-0.67	.506
Number of trials completed	-0.003	0.001	-2.88	.005*
Data completeness	-0.07	0.10	-0.73	.469
Conscientiousness (higher = greater consciousness)				
(Intercept)	-1.93	0.21	-9.13	<.001*
Conscientiousness traits	-0.002	0.002	-0.87	.388
Number of trials completed	-0.003	0.001	-2.88	.005*
Data completeness	-0.06	0.10	-0.57	.568
Proportion of time spent traveling				
Neuroticism (higher = greater neuroticism)				
(Intercept)	-1.09	0.62	-1.77	.077
Neuroticism traits	-0.01	0.04	-0.30	.762
Number of trials completed	0.01	0.003	3.31	<.001*
Data completeness	0.04	0.36	0.10	.922
Extraversion (higher = less extraversion)				
(Intercept)	-1.42	0.73	-1.95	.051

Extraversion traits	0.01	0.02	0.32	.750
Number of trials completed	0.01	0.002	3.33	<.001*
Data completeness	0.02	0.36	0.06	.951
Openness (higher = less openness)				
(Intercept)	-1.16	0.72	-1.62	.106
Openness traits	-0.002	0.02	-0.12	.907
Number of trials completed	0.01	0.003	3.28	.001*
Data completeness	0.01	0.36	0.03	.976
Conscientiousness (higher = greater consciousness)				
(Intercept)	-1.02	0.70	-1.45	.146
Conscientiousness traits	-0.003	0.01	-0.37	.714
Number of trials completed	0.01	0.003	3.29	<.001*
Data completeness	0.03	0.36	0.07	.934

*significant at $p < .05$ following Benjamini-Hochberg correction for multiple comparisons.

Table 5.

Choice Selectivity Predicted by Total OCPD Traits Measured Continuously.

Predictor	χ^2	p
Delay time as predictor of staying (0 = skip, 1 = stay)		
(Intercept)	8.59	.003*
OCPD traits	0.30	.583
Delay time	363.08	<.001*
Number of trials completed	36.27	<.001*
Data completeness	0.28	.599
OCPD traits * delay time	3.34	.068
Category rank as predictor of staying (0 = skip, 1 = stay)		
(Intercept)	56.85	<.001*
OCPD traits	1.65	.199
Category rank	1,498.75	<.001*
Number of trials completed	42.19	<.001*
Data completeness	0.18	.675
OCPD traits * category rank	11.69	.009*

*significant at $p < .05$ following Benjamini-Hochberg correction for multiple comparisons.

Table 5a.

Choice Selectivity Predicted by OCPD Traits Measured Categorically.

Predictor	χ^2	p
Delay time as predictor of staying (0 = skip, 1 = stay)		
(Intercept)	8.47	.004*
OCPD traits (0=lower 75%, 1=top 25%)	0.003	.953
Delay time	310.49	<.001*
Number of trials completed	36.44	<.001*
Data completeness	0.35	.552
OCPD traits * delay time	5.82	.016*
Category rank as predictor of staying (0 = skip, 1 = stay)		
(Intercept)	51.68	<.001*
OCPD traits (0=lower 75%, 1=top 25%)	0.89	.344
Category rank	1,105.73	<.001*
Number of trials completed	42.29	<.001*
Data completeness	0.25	.620
OCPD traits * category rank	12.38	.006*

*significant at $p < .05$ following Benjamini-Hochberg correction for multiple comparisons.

Table 5b.

Choice Selectivity Predicted by OCPD Trait Domains and Delay Time.

Predictor	χ^2	p
Delay time as predictor of staying (0 = skip, 1 = stay)		
Neuroticism (higher = greater neuroticism)		
(Intercept)	8.99	.003*
Neuroticism traits	0.79	.375
Delay time	363.75	<.001*
Number of trials completed	36.95	<.001*
Data completeness	0.31	.575
Neuroticism traits * delay time	5.83	.016*
Extraversion (higher = less extraversion)		
(Intercept)	8.62	.003*
Extraversion traits	0.14	.703
Delay time	362.76	<.001*
Number of trials completed	36.58	<.001*
Data completeness	0.29	.592
Neuroticism traits * delay time	0.67	.414
Openness (higher = less openness)		
(Intercept)	6.75	.009*
Openness traits	4.33	.037
Delay time	361.53	<.001*
Number of trials completed	36.47	<.001*
Data completeness	0.04	.839
Openness traits * delay time	0.90	.342
Conscientiousness (higher = greater conscientiousness)		
(Intercept)	9.09	.003*
Conscientiousness traits	<0.01	.955
Delay time	364.51	<.001*
Number of trials completed	36.04	<.001*
Data completeness	0.36	.550
Conscientiousness traits * delay time	7.05	.008*

*significant at $p < .05$ following Benjamini-Hochberg correction for multiple comparisons.

Table 5c.

Choice Selectivity Predicted by OCPD Trait Domains and Category Preference.

Predictor	χ^2	p
Category rank as predictor of staying (0 = skip, 1 = stay)		
Neuroticism (higher = greater neuroticism)		
(Intercept)	58.04	<.001*
Neuroticism traits	1.98	.159
Category rank	1504.23	<.001*
Number of trials completed	42.03	<.001*
Data completeness	0.21	.649
Neuroticism traits * category rank	4.65	.199
Extraversion (higher = less extraversion)		
(Intercept)	57.36	<.001*
Extraversion traits	2.20	.138
Category rank	1492.16	<.001*
Number of trials completed	41.97	<.001*
Data completeness	0.18	.671
Extraversion traits * category rank	19.36	<.001*
Openness (higher = less openness)		
(Intercept)	53.57	<.001*
Openness traits	5.31	.021*
Category rank	1498.74	<.001*
Number of trials completed	42.26	<.001*
Data completeness	0.02	.890
Openness traits * category rank	6.51	.089
Conscientiousness (higher = greater conscientiousness)		
(Intercept)	57.62	<.001*
Conscientiousness traits	0.748	.387
Category rank	1496.03	<.001*
Number of trials completed	42.16	<.001*
Data completeness	0.22	.642
Conscientiousness traits * category rank	24.55	<.001*

*significant following Benjamini-Hochberg correction for multiple comparisons.

Table 6.

Behavioral Adaptation predicted by Total OCPD Traits Measured Continuously.

Predictor	B	SE B	*t/z*	*p*
Likelihood of staying (0=skip, 1=stay)				
(Intercept)	2.63	0.47	5.60	<.001*
OCPD traits	0.16	0.18	0.90	.368
Past-trial ratings	0.99	0.06	16.77	<.001*
Number of trials completed	-0.05	0.06	-0.90	.368
Data completeness	-0.27	0.51	-0.53	.594
OCPD traits * Past-trial ratings	0.21	0.05	3.98	<.001*

*significant following Benjamini-Hochberg correction for multiple comparisons.

Table 6a.

Behavioral Adaptation Predicted by OCPD Traits Measured Categorically.

Predictor	B	SE B	*t/z*	*p*
Likelihood of staying (0=skip, 1=stay)				
(Intercept)	2.58	0.48	5.37	<.001*
OCPD traits (0=lower 75%, 1=top 25%)	0.25	0.43	0.58	.565
Past-trial ratings	0.84	0.06	13.56	<.001*
Number of trials completed	0.06	0.06	-1.02	.309
Data completeness	-0.31	0.51	-0.62	.536
OCPD traits * Past-trial ratings	0.65	0.16	4.13	<.001*

*significant following Benjamini-Hochberg correction for multiple comparisons.

Table 6b.

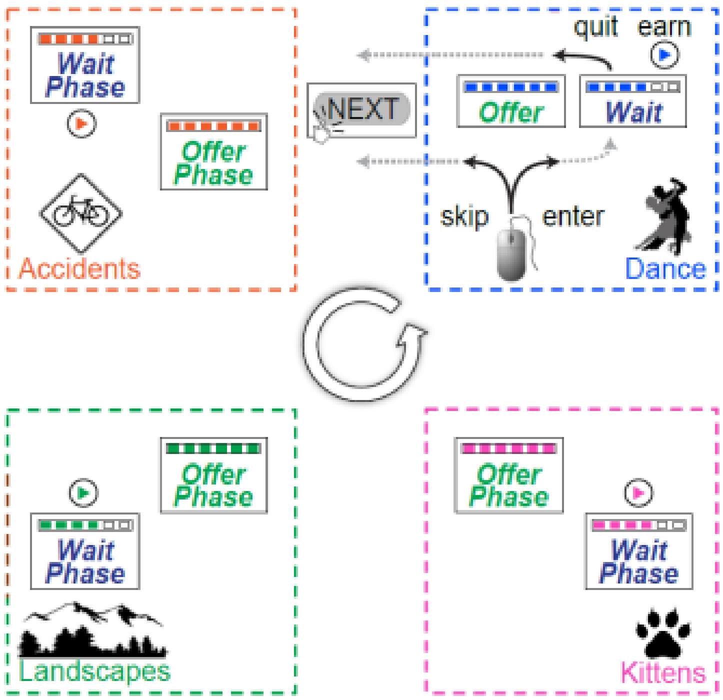
Behavioral Adaptation predicted by OCPD Trait Domains.

Predictor	B	SE B	*t/z*	*p*
Likelihood of staying (0=skip, 1=stay)				
Neuroticism (higher = greater neuroticism)				
(Intercept)	2.58	0.45	5.70	<.001*
Neuroticism traits	-0.24	0.17	-1.41	.158
Past-trial ratings	0.94	0.06	16.47	<.001*
Number of trials completed	-0.06	0.06	-1.00	.318
Data completeness	-0.25	0.49	-0.51	.610
Neuroticism traits * Past-trial ratings	0.12	0.06	2.16	.031
Extraversion (higher = less extraversion)				
(Intercept)	2.64	0.47	5.65	<.001*
Extraversion traits	0.17	0.18	0.97	.332
Past-trial ratings	0.97	0.06	16.66	<.001*
Number of trials completed	-0.05	0.06	0.88	.381
Data completeness	0.27	0.50	-0.54	.586
Extraversion traits * Past-trial ratings	0.11	0.05	2.20	.028
Openness (higher = less openness)				
(Intercept)	2.53	0.46	5.50	<.001*
Openness traits	0.37	0.18	2.10	.036
Past-trial ratings	0.97	0.06	16.55	<.001*
Number of trials completed	-0.05	0.06	-0.90	.367
Data completeness	-0.18	0.50	-0.36	.722
Openness traits * Past-trial ratings	0.10	0.06	1.75	.080
Conscientiousness (higher = greater consciousness)				
(Intercept)	2.63	0.47	5.60	<.001*
Conscientiousness traits	0.10	0.18	0.57	.572
Past-trial ratings	0.99	0.06	16.81	<.001*
Number of trials completed	-0.05	0.06	-0.86	.389
Data completeness	-0.27	0.51	-0.54	.587
Conscientiousness traits * Past-trial ratings	0.23	0.05	4.30	<.001

*significant following Benjamini-Hochberg correction for multiple comparisons

Figure 1.

Visual Depiction of the Web-Surf Task.



Note. Visual depiction of the Web-Surf task structure (Abram et al., 2016). Participants move through a virtual environment consisting of a series of video galleries. Before "entering" a gallery, the participant is presented with an "offer" consisting of the category of video (e.g., Dance, bike accidents, landscapes, or kittens) and a randomly-assigned delay time between 3 and 30 seconds. The participant can choose to "stay," or enter the gallery, wait through the delay, and watch the video, or "skip" to the next gallery. A "quit" decision occurs is the participant accepts an offer but decides to skip to the next gallery during the wait period. After viewing a video, participants rate their liking of the video on a scale from 1 (extremely dislike) to 5 (extremely like). Virtual "travel" between galleries requires the participant to click through a series of buttons corresponding to numbers randomly positioned on the screen.