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Temperament and Individual Differences in Category Learning

Tianshu Zhu, *The University of Western Ontario*

Supervisor: John Paul Minda, *The University of Western Ontario*

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Abstract

Objectives. Individuals can differ in their strategic approach in learning the same categorization task, researchers have sought to study what specific stable individual differences traits can help explain these differences. This dissertation first surveyed extant literature on the impact of trait differences on category learning then examined the effect of temperament traits on these dependent variables. *Chapter 2 (scoping review):* This scoping review synthesized the past literature that examined the relationship between sources of stable individual differences and category learning performance and strategy use outcomes. Five database platforms were searched to identify relevant articles, cross-referencing was also performed. Sixty-nine studies met inclusion criteria with 3 major sources of individual differences identified: (1) developmental, (2) aging, (3) working memory. The results of this scoping review suggest that (1) children tend to show both performance and task-appropriate strategy-use disadvantage in both rule-based and similarity-based category learning tasks compared to young adults. (2) Older adults also showed a performance disadvantage, but results were less consistent with regards to whether they used different strategies than young adults. (3) Working memory was associated with better performance on both types of tasks, but it was not associated with strategy choice on rule-based tasks, and results were inconsistent in terms of strategy choice on similarity-based tasks. *Chapter 3 (two studies):* In two studies, I examined affective temperament traits to see whether the tendency to experience negative and positive affect is predictive of category learning performance and strategy use. Temperamental effortful control and working memory were measured as covariates. There were minimal effects of affective temperament traits and temperamental effortful control may be negatively associated with learning on both types of category learning. Working memory may be positively associated with learning on both types of category learning. However, these findings were not consistent across studies. The results may either reflect a lack of relationship or low data quality due to the pandemic. *Conclusions:* Neither previous studies nor the present dissertation provided a firm answer to the mystery behind individual differences in category learning strategy use. Future research should replicate the studies in Chapter 3 of this dissertation in the laboratory to see whether temperament effects would emerge.

Keywords

Temperament, Individual Differences, Cognition, Category Learning, Working Memory, Scoping Review, Online-Based

Summary for Lay Audience

People use a variety of strategies when learning the same category, despite the fact that only one strategy yields high performance. This curious phenomenon has spurred the interest of researchers to want to understand if certain characteristics can predict the specific strategy a person tends to use. This dissertation explores the effect of temperament traits as potential predictive characteristics through two projects. In the first project, an overview of existing research studies that examined the impact of different characteristics on category learning was provided. Three characteristics were particularly studied: brain development of children, healthy aging of adults, and the ability to hold and manipulate information in the brain. I found that children tend to use a strategy that gives them lower performance compared to young adults. Older adults also suffer from lower performance than young adults, but the two groups may not differ in their choice of strategy. Higher ability to hold and manipulate information in the brain has been associated with better performance but not consistently with the better strategy. In the second project, participants self-rated on a questionnaire which measures their temperament traits and they also completed category learning tasks. Three temperament traits were of interest: tendency to experience positive emotions, tendency to experience negative emotions and the ability to focus and control attention. I also measured the ability to hold and manipulate information since it was found to lead to better performance. I did not find a consistent relationship between any temperament traits or the ability to hold and manipulate information with category learning. These results suggest either an actual lack of relationship or that data collected during the pandemic may have had low quality and hid the real effect. More research is needed to further study the effects of temperament traits on predicting category learning performance and strategy.

Co-Authorship Statement

Chapter 2 of this dissertation is a scoping review that required multiple reviewers. Two reviewers (Tim Qiu and I) independently conducted abstract screening, and disagreements were resolved by a third reviewer (Ana Ruiz Pardo). Full text-review and data charting was first done by me and then reviewed by Ana Ruiz Pardo. Tim Qiu was addressed in Chapter 2 as TQ, and Ana Ruiz Pardo was addressed in Chapter 2 as ARP.

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1. Chapter 1 - General Introduction

1.1. Introduction

1.1.1. Category Learning

Categorization is a fundamental phenomenon of cognition and intelligent behaviour. The mental representations of categories are called concepts and these are the core building blocks of the knowledge we have about the world. Understanding categorization is an important step toward understanding cognition. Categorization is not only critical to our day-to-day activities (e.g., identify food items from non-edible items), it is also a learned skill that is heavily involved in many professional fields such as radiology (Hatala et al., 2003) and forensics (Searston & Tangen, 2017). Understanding how people group objects together is an essential step in identifying ways to enhance the learning process and enable better categorical knowledge transfer or generalization. Knowledge transfer is the ultimate purpose of categorization, which allows us to make inferences based on the category membership and react accordingly without having to experience every single object. Category learning is a model-rich field, its main emphasis has been on developing computational models to account for people's strategic approach in their categorization responses. The goal of this dissertation is to explore the ways in which individual differences in temperament traits can lead to variations in category learning.

Dual-process Theories of Category Learning

Steven Sloman (1996) proposed a version of dual-process theory within the judgment and decision making literature. This account followed a parallel-competitive architecture -- the associative (automatic) and rule-based (analytic) processing occur in parallel and compete to find the solution. A number of related dual-process models have also been proposed in category learning research (Anderson & Betz, 2001; Ashby et al., 1998; Bott & Heit, 2004; Erickson & Kruschke, 1998). These models contend that categories can be learned either through an explicit rule-based system or an implicit similarity-based system. One of the most researched multiple systems models of category learning is the COmpetition between Verbal and Implicit Systems (COVIS) model. It postulates that the explicit and implicit systems compete throughout learning, much aligned with Sloman's account. The explicit system requires hypothesis testing of verbalizable rules and effortful working memory engagement, whereas the implicit system operates effortlessly and is associated with procedural learning (e.g., Ashby et al., 1998). Compared to the consensus with regards to the nature of the explicit system, there have been debates around whether the implicit system relies on exemplar-based memorization (e.g., Brooks, 1978; Estes, 1986; Medin & Schaffer, 1978; Nosofsky, 1986), prototype abstraction (e.g., Homa et al., 1981; Minda & Smith, 2001; Reed, 1972) or procedural-based cognitive mechanisms (e.g., Ashby & Gott, 1988; Ashby & Lee, 1991; Ashby & Maddox, 1990, 1992, 1993).

Evidence supporting the dissociation between the explicit and implicit systems has mostly come from category learning tasks whose stimuli and structures can be best learned through either an explicit process or an implicit process (cf. Erickson, 2008). These tasks originated from decision bound theory which assumes that people learn to associate category space partitioned by the decision bound(s) with particular category responses (Ashby & Gott, 1988; Ashby & Maddox, 1993; Ashby & Townsend, 1986). Certain decision bounds are easily verbalizable in relation to stimulus dimensions, resulting in the development of rule-based category structures. Other decision bounds cannot be easily described in terms of stimulus dimensions, resulting in the development of similarity-based category structures. In a typical rule-based category learning task, learners need to identify and attend to the only relevant stimulus dimension (the rule), and then map each dimension value to different category labels (Ashby & Maddox, 2005). Formulation of an explicit verbal rule relies on analytic resources (Hayes-Roth, 1985). Learning multidimensional rules such as the conjunction and disjunctive rules also require analytical processing of relevant stimulus dimensions. On the other hand, similarity-based category learning requires learners to combine several stimulus dimensions to derive at a category decision, and the stimulus often needs to be processed as a gestalt (Ashby et al., 1998). Not surprisingly, this information integration approach overlaps with global holistic processing and procedural learning (Navon, 1977; Kimchi, 1992). Many studies have used explicit and implicit category structures based on the decision-bounds and found dissociations between the two types of structures in terms of the underlying process that mediated optimal learning (Ashby et al., 1999, 2002, 2003; Ashby & Waldron, 1999; Maddox et al., 2003; Smith et al., 2014). Dissociation between the explicit and implicit systems is evident when differential behavioral outcomes were elicited in the rule-based and similarity-based categorization tasks by the same experimental manipulation. For instance, Ashby et al. (2002) showed that training type (i.e., observation vs. feedback) affected the similarity-based category structure much more than the rule-based category structure. Smith et al. (2014) found that deferred feedback significantly impacted similarity-based category learning but spared rule-based category learning.

Individual Differences in Category Learning and Strategy Use

Interestingly, despite the average patterns described above, ample studies have shown that individuals can differ in their strategic approach in learning the same task (Ashby et al., 1998; Donkin et al., 2015; Meeter et al., 2006; Minda & Smith, 2001; Nosofsky & Zaki, 2002; Pelley et al., 2019; Raijmakers et al., 2001; Wills et al., 2015). For example, a subgroup of participants may show a strong tendency or preference for rule use and apply this strategy to a similarity-based category learning task despite having lower performance accuracy than people who used the task appropriate strategy. There are limitations to drawing conclusions about the underlying mechanisms of category learning based on average patterns of performance while overseeing the qualitative differences across participants (Lee & Webb, 2005; Navarro et al., 2006; Siegler, 1987). Discovering the factors associated with using different strategies and dividing participants based on these should be a critical first step before conducting analysis on learning mechanisms.

There has been ample research on a variety of clinical populations that demonstrated deficits in learning the optimal category learning strategy (Ashby et al., 1998; Filoteo et al., 2014; Helie et al., 2011; Shohamy et al., 2004). However, few studies have examined the traits behind individual differences in category learning strategy use among the healthy population. Among the individual differences traits being examined by these studies, few if any has been shown to consistently predict strategy choice. Chapter 2 of this dissertation is a scoping review of the current literature on stable trait differences and category learning. It demonstrated the inconsistency among research findings with regards to predictive factors of categorization strategy use. Results from the review suggest additional factors need to be explored. Below, I discuss previous evidence that provided me with insights and rationale to test a novel set of traits and their relationship with strategy preferences.

1.1.2. Executive Attention and Working Memory

Prior research has shown that age-related changes in cognition can impact individuals' performance and strategy use on rule-based and similarity-based category learning tasks. Rabi and Minda (2016) showed that older adults performed significantly worse than young adults on both the task that required discovery of a complex rule (disjunctive rule-based category structure) and the task that required similarity-based processing (information integration category structure). Older adults tended to rely more on suboptimal single-dimensional rule in the disjunctive rule-based category, and they were less consistent in applying the similarity-based strategy in the information integration category. Maddox et al. (2010) also found that normal aging impacts both types of category learning and this may be resulted from diminished inhibitory control. Along the same line, Racine et al. (2006) found that older adults performed on par with younger adults on the single-dimensional rule-based task, but showed deficits when the rule became complex. Minda and colleagues ((2008); (Rabi & Minda, 2014)) showed that young children similarly showed lower performance in learning more complex rule-based strategies, but their performance did not differ from young adults in learning simple rules and similarity-based strategies. Studies have compared young children and adults' strategy-use in learning ambiguous categories and found that children relied mostly on overall similarity, while adults tend to rely on the deterministic rule (Deng & Sloutsky, 2016; Miles & Minda, 2009). These studies showed that young adults have an advantage learning complex rule-based categories than young children and older adults, but the learning advantages were less consistently observed in similarity-based tasks.

These observed behavioral differences can be attributed to neurophysiological changes across the lifespan. Neuroimaging studies have shown that rule-based cognitive tasks engage the prefrontal cortex and task-related activations in the head of the caudate nucleus and the anterior cingulate have also been reported (Konishi et al., 1999; Lombardi et al., 1999; Rao et al., 1997; Rogers et al., 2000; Volz et al., 1997). These are critical components of the structures relating to working memory (Gabrieli, 1995; Goldman-Rakic, 1995a, 1995b) and the executive attention system (Miller & Wickens, 1991; Posner & Petersen, 1990). Executive attention is considered to be a component of working memory by Engle and colleagues, this component is defined as the ability to select and maintain task goals and avoid distraction (Engle & Kane, 2004). The other component of working memory is storage (Baddeley, 2012). The prefrontal cortex along with other areas underlying executive attention takes many years to fully develop during normal growth, therefore, young children (e.g., younger than 5 years old) often have difficulty with selectively attending to the relevant stimulus dimension(s) when testing or applying a rule (Hanania & Smith, 2009; Plude et al., 1994), as well as with remembering and shifting attention to untested rules (Aschkenasy & Odom, 1982; Gholson et al., 1972; Kemler, 1978). The deficits seen in older adults can also be attributed to diminishing activities in the structures related to executive attention. Older adults had more difficulty than young adults with resolving conflicts within tasks and inhibiting task-irrelevant behaviors (Davidson et al., 2003; May & Hasher, 1998; West, 1999; Williams et al., 1999), which demonstrated compromised executive attention. The decline in working memory storage is also evident in older adults, reflected both through verbal and spatial aspects (Bopp & Verhaeghen, 2005; Park et al., 2002).

Studies that examined category learning in healthy young adults have shown mixed results with regard to working memory. Lewandowsky et al., (2012) showed that working memory capacity mediated the performance on all types of category structures. Similarly, Kalish et al., (2017) found that individuals with higher working memory capacity tended to perform more accurately on both rule-based and similarity-based category learning tasks. Studies have also shown that higher working memory capacity was associated with faster learning on both rule-based tasks and similarity-based tasks, as well as more task appropriate strategy use on the similarity-based task (Carlson, 2009; Craig & Lewandowsky, 2012). McDaniel et al. (2014) used a variety of category generalization tasks to investigate whether an individual's tendency to use explicit or implicit processes was related to a number of cognitive capacities. They found a positive relationship between working memory and the tendency to use rules. On the other hand, other studies have failed to find a relationship between working memory and category learning strategy use. Wang et al. (2015) found that the shifting component of executive functions was related to category learning performance, but neither executive attention nor memory storage component of working memory was found to be associated with categorization strategy use. Kalish et al. despite finding a memory and performance relationship, did not find working memory capacity to be predictive of categorization strategy use. Goldwater et al. (2018) and Little and McDaniel (2015) similarly failed to show an association between higher working memory and a preference for rule.

Taken together, results suggest that higher executive attention is associated with better performance, especially on complex rule-based category learning. Working memory in general was shown to be predictive of better performance on both rule-based and similarity-based tasks. However, neither executive attention alone nor the general concept of working memory capacity was found to be consistently predicting the preference for one strategy over another.

1.1.3. Transient Affect

Evidence from Category Learning

Ashby and colleagues (Ashby et al., 1998, 1999) proposed the dopaminergic theory of positive affect, which argues that the effects of positive affect on cognition are mediated by dopamine. It also assumes that increase of dopamine release in the anterior cingulate cortex and prefrontal cortex during transient positive mood states increases cognitive flexibility and verbal fluency. Ashby and colleagues suggest that positive affect facilitates explicit rule-based learning and implicit similarity-based learning. Cognitive flexibility and verbal fluency are related to rule selection and rule switching (Owen et al., 1993), thus improving the efficiency of discovering the optimal strategy. The dopaminergic theory further postulates that striatal dopamine is critical in mediating feedback in procedural learning (Ashby et al., 2007). Positive affect facilitates similarity-based tasks through projecting dopamine into the striatum, a critical region involved in this type of processing. Moreover, cognitive flexibility may also speed up the process of exhausting potential rule-based strategy before resorting to the similarity-based strategy. Based on the dopaminergic theory, positive affect should facilitate both rule-based and similarity-based category learning, while negative affect, although having an arousal component, should not affect these learning processes. Empirical evidence has supported the dopaminergic theory on its assumption that positive mood facilitates rule-based category learning, but results were less consistent with regard to similarity-based category learning. Nadler et al. (2010) found that positive mood facilitated optimal strategy discovery on both rule-based and similarity-based category learning tasks, but significant performance difference between mood states was only observed in the rule-based task. Nielsen & Minda (2018) found positive mood significantly facilitated learning on the rule-based categorization task, but they did not find any mood effects on learning of the similarity-based task.

The dopaminergic theory holds a prominent position within category learning literature. However, it is worth noting that research around affect generally falls in the realm of social psychology, so I examined the literature for additional insights of the affect and cognition relationship.

Evidence from Social Cognition

One prominent theory originated from social psychology that tries to explain the association between affect and processing style is the affect-as-information hypothesis. This theory proposes that people rely on their mood to guide judgment, decision-making and information processing (Clore, 1992; Schwarz & Clore, 1983). Positive affect signifies a safe environment and promotes a focus on internally accessible information. Negative affect signifies a problematic environment which promotes a focus on gathering and analyzing external information in order to regain wellbeing (Clore et al., 2001). Internally focused approaches tend to be intuitive and implicit, while externally focused approaches tend to be analytical and explicit. Gasper and Clore (1998) found that people high in trait negative affect have difficulty parsing out their emotional feelings from information processing. It can be speculated that these individuals are chronically in the mode of vigilance and analysis. Several studies have shown that negative affect, such as anxiety and stress can trigger an effortful, analytical processing style (Clark & Isen, 1982; Isen, 1987). Studies on positive mood and cognition are also abundant and findings indicate that people in a good mood tend to reach decisions more quickly, use less information, and avoid analytical thinking (Ashby et al., 1999; Bless et al., 2006; Fiedler, 2001; Fredrickson, 2009; Hertel & Fiedler, 1994; Isen & Daubman, 1984). Moreover, implicit holistic processing has been shown to make people happier than local processing (Akbari Chermahini & Hommel, 2012; Ji et al., 2019). Therefore, the relationship between affect and processing style is bi-directional and consistent. According to the affect-as-information framework, positive mood promotes implicit processing which benefits similarity-based category learning, and negative mood promotes explicit processing which benefits rule-based category learning.

1.1.4. Temperament Traits

Allport (1937, p. 54), a founder of the trait-based approach to personality, stated that "temperament refers to the characteristic phenomenon of an individual's emotional nature…dependent on constitutional make-up". The term 'constitutional' links temperament to underlying psychobiological systems and genetics. This definition is appealing because researchers can map temperament domains to underlying neurobiological systems to study their development and interaction. Rothbart and Derryberry (1979, 1981) similarly defined temperament as constitutionally based individual differences in reactive emotions and his or her ability to control them. These together form the basis of adult personality traits (Rothbart, 2012). Personality traits, on the other hand, extend to broader domains such as individuals' attitude and specific thought contents (Rothbart & Bates, 2007). Temperament plays a critical role in the development of emotional experiences throughout the entire lifespan, from childhood (Rothbart, 2007) to old age (Mehrabian & Blum, 1996). Evans and Rothbart (2007) developed the Adult Temperament Questionnaire (ATQ) that measures four temperament traits: negative affect, extraversion/surgency, effortful control, and orienting sensitivity. This study focused on the first three traits. The negative affect, extraversion/surgency and effortful control temperament traits map onto personality traits Neuroticism, Extraversion and Conscientiousness dimensions within the Big Five and Big Three scales of adult personality, respectively (Ahadi & Rothbart, 1994; Evans & Rothbart, 2007; Rothbart et al., 2000).

Affective Temperament Traits vs. Affective States

The negative affect and extraversion/surgency traits are related to emotional reactivity and refers to the tendency to experience negative and positive affect, respectively. Previous studies have uncovered certain structural and functional correlates of affective temperament traits. Much of this evidence suggests that individuals with certain affective temperament traits (e.g., high trait negative affect) show higher resting state activities in relevant brain regions in much the same way as during elicited transient affect (e.g., negative affect). Transient negative affect has been shown to be associated with increased amygdala activation, both when participants were exposed to aversive stimuli (Zald, 2003) and asked to maintain negative mood (Davidson et al., 1999; Schaefer et al., 2002). Amygdala activation was seen during resting state in individuals who self-rated high on trait negative affect (Davidson & Henriques, 2000). Similarly, patients with anxiety related disorders who experience chronic negative affect consistently show increased amygdala activation during resting state (Drevets, 1999). Liotti et al. (2000) showed that transient negative affect was correlated with decreased activation of the right dorsal-lateral prefrontal cortex in the healthy population. This reduction in activity and volume was similarly seen in patients who suffer from chronic negative mood symptoms (Drevets). Harmon-Jones and Allen (1997) found increased activity in the left dorsolateral prefrontal cortex to correlate with trait positive affect. Moreover, Liotti and colleagues also showed that negative mood results in increased activity in the ventral anterior cingulate cortex (ACC), and individuals who self-reported high in trait negative affect demonstrated higher resting activity in this region (Zald et al., 2002). Activity in the ACC is also related to trait positive affect. The ACC is the core brain region involved in reward-related dopaminergic systems, the functions of dorsal ACC are related to motivation and positive affect (Allman et al., 2001). Previous research has shown that lesions or reduced activity of the dorsal ACC are related to the lack of pleasure and motivation in psychiatric patients with chronic negative affect (Sigmundsson et al., 2001).

As we can see, structural and functional studies of the cortical regions related to affective traits have provided evidence for an association with transient affective states. People with specific temperament traits (e.g., high trait negative affect and low trait extraversion/surgency) tend to have baseline activity in the relevant brain regions in much the same way as experiencing a specific mood (e.g., negative affective state). Therefore, it is reasonable to expect affective temperament traits to be predictive of category learning behaviors based on results on affective states.

Temperamental Effortful Control

Temperament is relatively stable, but it may not fully stabilize until preschool years. This can be attributed to the brain's development of the executive attention system (e.g., lateral prefrontal cortex, and anterior cingulate cortex), which corresponds to the emergence of temperament trait of effortful control (Rothbart et al., 1994; Rueda, 2012) and coincides with children's ability to apply explicit rule-based strategies in category learning (Deng & Sloutsky, 2016; Rabi & Minda, 2014). The effortful control trait refers to the capacity to self-regulate, including attention control such as voluntarily focusing and shifting attention (Rothbart & Bates, 2007; Rothbart & Rueda, 2005). The construct of effortful control originated from social psychology. Compared to similar constructs from cognitive psychology such as cognitive control, it has a particular emphasis on socioemotional and adaptive functioning (Zhou et al., 2012). Effortful control has been shown to modulate the effects of emotional reactivity. Individuals high in negative affect are less likely to display problems when they have high effortful control (Rothbart & Bates, 2007; Rothbart & Posner, 2006). Similarly, ineffective temperamental effortful control has been shown to be related to the development of depressive symptoms (Laceulle et al., 2014; Loukas & Robinson, 2004; Marchetti et al., 2018). In line with this, Drevets and Raichle (1998) showed that when effortful control is strengthened, the affective activities tend to be reduced. Posner and Rothbart have argued that the same brain regions (lateral prefrontal cortex, and anterior cingulate cortex) related to the executive attention network also support effortful control (Posner et al., 2007; Posner & Rothbart, 2007). Whittle et al. (2008, 2009) also indicated that individual differences in effortful control are related to the structural and functional variations in the neural substrate corresponding to the executive attention network. Individuals' with higher effortful control also tend to perform more efficiently on cognitive tasks involving visual or spatial conflicts (i.e., Stroop, flanker or Simon; Rothbart & Bates, 2007).

1.1.5. Temperament Traits and Potential Implications for Category Learning

Temperament traits have been widely studied in clinical and social psychology as potential risk factors for developing mental disorders (Jones et al., 2014; Laceulle et al., 2014; Lucey et al., 2019; Marchetti et al., 2018; McKinney et al., 2020), but their implications in cognitive psychology were less examined. Temperament is composed of a collection of traits with two common components: emotional reactivity and emotional regulation. Both positive and negative affect are aspects of emotional reactivity (Spinrad et al., 2004), whereas emotion regulation encompasses the process of modulating the intensity of emotional arousal (Thompson, 1994). These two components are co-occurring and the possibilities for interactions are high (Campos et al., 2004). I have illustrated in previous sections the structural and functional similarities between affective traits and affective states in the brain, as well as demonstrated that temperamental effortful control and executive attention are similar constructs arising from different fields of psychology. To my knowledge, despite there being a promising potential, little to no research has been done to investigate the relationship between individual differences in temperament traits and people's preferences in category learning strategy.

1.1.6. Overview of Dissertation

In Chapter 2, I conducted a scoping review of empirical studies published between 2000 and 2021 that examined the effects of individual differences in stable traits on people's category learning behaviors. I sought to ensure through this exhaustive search that no work of similar nature has been done in the past and at the same time develop an understanding of the trait effects that were previously studied. To preview the results, no previous study has looked at whether temperament traits are associated with the tendency to use rule-based or similarity-based strategy. The majority of the reviewed studies focused on developmental changes of executive functions and individual differences in working memory. While there was a general consensus that higher executive functions and working memory tend to be associated with better performance on both rule-based and similarity-based tasks, results relating to strategy choice were less consistent.

In Chapter 3, I examined the relationship between temperament traits and category learning behaviors through two empirical studies. Another goal of this chapter is to compare the two previously mentioned theories: dopaminergic theory and affect-as-information hypothesis, and to see which theory generated hypotheses that are more aligned with the results. Both studies in Chapter 3 included a conjunctive rule-based task and a similarity-based task[1]. In Experiment 1, I used a decision bound paradigm for the categories. This paradigm is associated with the decision-bound analysis which assumes that strategies can be modeled by a linear decision boundary that divides the category space (Ashby & Gott, 1988; Soto & Ashby, 2015). It allows me to detect the specific strategy used by each participant. In Experiment 2, an extended trials-to-criterion (TTC) design was devised to also look at participants' rate of learning the task appropriate strategy and overall performance. The TTC task was adapted from Xie et al. (2015). Due to the high number of non-learners, I also analyzed the overall performance as an additional measure of learning irrespective of the strategy used. The main difference between the paradigms used in experiment 1 and 2 is that stimuli on the decision bound task varied on continuous dimensions while stimuli on the TTC task varied on binary dimensions.

Based on the dopaminergic theory, I hypothesized that higher trait extraversion/surgency would be associated with an advantage in learning both the rule-based and similarity-based task. This should be reflected through higher performance and more optimal strategy use. Moreover, different scores on trait negative affect alone should not affect people's performance on either of the tasks.

On the other hand, if the affect-as-information framework was true, individuals with higher extraversion/surgency would only show higher performance and more optimal strategy use on the similarity-based task, whereas people with higher negative affect would be associated with an advantage in learning the rule-based task through the same measures. I also hypothesized that temperamental effortful control would modulate the biased effects of affective temperament on cognition, and facilitate better category learning performance on both types of tasks.

[1] Due to the pandemic lockdown, both experiments were conducted online.

Neither affective temperament trait was significantly predictive of category learning performance or strategy in Experiment 1. Negative affect and Extraversion were both associated with lower similarity-based task performance in Experiment 2. The overall picture was not aligned with either theory of affective state. Contradictory to my hypothesis, effortful control negatively contributed to the overall performance on both rule-based and similarity-based category learning tasks. Effortful control modulated the biased processing associated with affective traits, but these modulations were not entirely facilitatory. In addition, inconsistent results relating to working memory added another layer of perplexity to the already mixed existing evidence as discussed in the scoping review. Taken together this dissertation showed that neither previously studied traits nor temperament traits consistently predict category learning strategy preference, this phenomenon remains elusive.

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2.Chapter 2 - Individual Differences and Category Learning - A Scoping Review[2]

This scoping review synthesizes the past literature that examined the relationship between sources of stable individual differences and category learning performance and strategy use outcomes. PsycInfo (ProQuest), PubMed, Web of science, Scopus and gray literature platforms were searched to identify relevant articles, cross-referencing was also performed. Sixty-nine studies met inclusion criteria with 9 sources of individual differences identified: (1) developmental, (2) aging, (3) cognitive capacities, (4) genetic variations, (5) culture, (6) expertise, (7) iron deficiency, (8) threat appraisal, (9) personality. However, only the first 3 themes were well studied where the results can be summarized and synthesized. The results of this scoping review suggest that (1) children tend to show both performance and task-appropriate strategy-use disadvantage in both rule-based and similarity-based category learning tasks compared to young adults. (2) Older adults also showed a performance disadvantage, but results were less consistent with regards to whether they used different strategies than young adults. (3) Working memory was associated with better performance on both types of tasks, but it was not associated with strategy choice on rule-based tasks, and results were inconsistent in terms of strategy choice on similarity-based tasks. (4) Specific genetic variations can put people at an advantage in learning certain types of categorization tasks.

Keywords: *individual differences, learning strategy, category learning, working memory*

2.1. Introduction

Arksey and O'Malley (2005) identified four reasons for conducting a scoping study: 1) to examine the extent, range and nature of research activity; 2) to determine the value of undertaking a full systematic review; 3) to summarize and disseminate research findings; 4) to identify research gaps in the existing literature. The present scoping review addressed all four aspects. It mapped the existing literature in the field of individual differences in category learning in terms of the volume, nature and characteristics of experiments. There has not been another review that examined the ways in which different stable traits have been linked to variations in category learning. Category learning literature has been vast and heterogeneous in nature, this scoping review is the first attempt to provide a rigorous and transparent mapping of one topic within this area of research.

[2] We followed open science practice for this scoping review. The data chart and summarized results for this review are available at (https://osf.io/2an3c/) and the protocol of this review was pre-registered at (https://osf.io/je3yz).

Background and Rationale

Categorization is a fundamental skill across all areas of life, from doing daily chores such as sorting laundry to recreational activities such as fishing for specific species of fish. The essence of constructing a category is to formulate knowledge that can be generalized beyond the few examples that are learned. The mental representations of categories are called concepts and these are the core building blocks of the knowledge we have about the world. In other words, understanding categorization behavior is the first step to understanding cognitive processes. Within the research field of category learning, a great deal of interest has been focused on understanding and modelling the ways in which categories are learned.

A number of category learning models have been proposed (Anderson & Betz, 2001; Ashby et al., 1998; Bott & Heit, 2004; Erickson & Kruschke, 1998; Smith et al., 1998). Many of these models contend that categories can be learned either through an explicit rule-based system or an implicit similarity-based system. The explicit system requires hypothesis testing of verbalizable rules and effortful working memory engagement, whereas the implicit system operates effortlessly and is associated with motor learning (e.g., Ashby et al., 1998). Compared to the consensus with regards to the nature of the explicit system, there have been debates around whether the implicit system relies on exemplar-based memorization (e.g., Brooks, 1978; Estes, 1986; Medin & Schaffer, 1978; Nosofsky, 1986), prototype abstraction (e.g., Homa et al., 1981; Minda & Smith, 2001; Reed, 1972) or procedural-based cognitive mechanisms (e.g., Ashby & Gott, 1988; Ashby & Lee, 1991; Ashby & Maddox, 1990; Ashby & Maddox, 1992, 1993) .

Rule-based and similarity-based category learning tasks have been developed that specifically aim to engage either the rule-based or similarity-based system (cf. Erickson, 2008). In a typical trial of a category learning task, a participant classifies a stimulus into one of two categories. In a rule-based task, the two categories can be defined by a verbalizable rule (e.g., red objects belong to category A; green objects, category B). The participant needs to conduct hypothesis testing with each potential rule until the optimal rule is discovered. In a similarity-based task, the optimal strategy cannot be described verbally, which means hypothesis testing for a verbalizable rule would not work. Instead, the participant needs to examine each stimulus holistically and compare it with previously shown category exemplars before arriving at a categorization decision based on within category similarity. A real life example of similarity-based categorization is to judge whether a large furry animal in an off-leash hiking trail is a pet dog or a coyote[3]. Categorization researchers have been focused on both performance accuracy and strategy use in these types of tasks as indicators of people's category learning capacities. In this review, the terms rule-based and similarity-based can be used to describe both the structures of category learning tasks, as well as the strategic approaches used by participants.

[3] There is a fairly good and verbalizeable rule to tell the difference: the coyote has a straight down pointing tail. However, most people cannot see the tail, and not everybody knows this rule. Our reliance tends to be based on similarities to a few exemplars.

Interestingly, previous studies have shown that individuals may differ in their strategic approach in learning either the rule-based or similarity-based categories (Donkin et al., 2015; Minda & Smith, 2001; Pelley et al., 2019). For example, a subgroup of participants may show a strong tendency or preference for rule use and apply this strategy to a similarity-based task despite having lower performance accuracy than people who used the task appropriate strategy. Several studies have examined potential reasons behind performance and strategy use differences among participants, one popular venue is through experimentally manipulating participants' cognitive capacities and studying its effects. However, these studies have generally overlooked pre-existing stable traits within participants that may have already differentiated them from one another in terms of their approach to categorization. Understanding the stable trait factors that are associated with suboptimal category learning is the first step towards identifying ways to promote optimal performance and effective knowledge transfer.

In this scoping review, we explore the sources of stable individual differences that affect people's category learning performance and strategy use. Although previous reviews exist in the area of category learning, these have focused on the effects of task differences on learning (Hughes & Thomas, 2021), neural systems involved in category learning (Ashby & Maddox, 2005; Ashby & Spiering, 2004; Ashby & Maddox, 2011; Seger & Miller, 2010), or categorization behaviour in cognitively impaired populations (Filoteo et al., 2017; Mercado et al., 2020). The current review synthesizes existing literature to explore relationships between various sources of stable traits and differential categorization performance and strategies seen among learners.

2.2. Methods

We conducted a scoping review following the methodological framework developed by Arksey and O'Malley (2005) and guidelines for conducting scoping review from the Joanna Briggs Institute (JBI; Peters et al., 2019). We adhere to the recommendations of (Colquhoun et al., 2014) and aim to synthesize previous research evidence and to identify gaps in the literature. We followed the 9 steps of the JBI guidelines: 1) define and align the objective and research question; 2) develop and align the inclusion criteria with the objective and research question; 3) describe the planned approach to evidence searching, selection, data extraction and presentation of the evidence; 4) search for the evidence; 5) selection of evidence; 6) extracting the evidence; 7) analysis of the evidence; 8) presentation of the results; 9) summarize the evidence in relation to objective, make conclusion and provide implications. The primary research question of this scoping review is: "What individual differences factors are associated with differential performance or strategy use in learning rule-based or similarity-based categories, and in what way?"

2.2.1. Protocol and Registration

The protocol for this scoping review has been preregistered on OSF at https://osf.io/je3yz.

2.2.2. Inclusion and Exclusion Criteria

We included studies that use experimental or quasi-experimental designs to compare category learning performance and strategy use among groups that differ on some aspect of stable traits. The age of participants in the studies ranges from young children (> 4 years) to older adults. Age-appropriate cognitive development and healthy cognitive status is required. Clinical populations and individuals with impaired cognitive functions are not included. An eligible study should use one or more categorization task(s) that can be learned through a rule-based or a similarity-based strategy, or both. The terms 'categorization task' and 'category learning task' will be used interchangeably in the remainder of this scoping review. A rule-based strategy is an approach that can be easily described by the learner (e.g., red objects belong to category A, green objects belong to category B). On the other hand, the learner would have difficulty describing their strategy verbally if it was similarity-based. This approach requires the learner to base categorization on overall similarity of objects rather than one or more salient features. The categorization task can be in any modality, such as visual, auditory or speech. Feedback to categorization responses can be present or absent. Eligible studies were those written entirely in English, and were made available between 2000 and 2021. We excluded any studies that create differences between groups through experimental manipulation; only studies that investigated intrinsic stable trait differences were included.

2.2.3. Search Strategy and Search Terms

A comprehensive first search strategy was developed based on the number of results returned from the primary database -- PsycINFO (ProQuest). This was to ensure that the evidence yielded is neither too narrow nor too broad.

The first official search strategy for PsycINFO (ProQuest) is shown below. This search was conducted on April 22nd 2021

> ti(categorization OR category learning) AND noft(rule OR abstraction OR explicit OR implicit OR procedural OR memorization OR global OR local OR broad OR narrow OR strategy OR analytic OR heuristic OR intuitive) NOT noft(animal OR medical OR computer OR words OR faces OR intervention OR social OR semantic OR social OR linguistic OR gender OR management OR public OR physiology)

The second search strategy with additional keywords for PsycINFO (ProQuest) is shown below. This search was conducted on May 13th 2021

> ti(categorization OR category learning) **AND noft(culture OR preference OR individual differences)** AND noft(rule OR abstraction OR explicit OR implicit OR procedural OR memorization OR global OR local OR broad OR narrow OR strategy OR analytic OR heuristic OR intuitive) NOT noft(animal OR medical OR computer OR words OR faces OR intervention OR social OR semantic OR social OR linguistic OR gender OR management OR public OR physiology)

Identical search strategies were also applied to 3 other databases (PubMed, Web of science, Scopus) at both of the time points. Keyword search was also conducted with unpublished literature databases (i.e., ProQuest Dissertation and Thesis Global, PsyArXiv) and potential relevant articles were manually selected. Reference lists of the included papers after full-text review were searched for additional articles based on title relevance, articles that cited the included papers were also examined. This interactive process continued for each newly added article. Articles that were deemed relevant at this stage will be directly imported to the full-text review stage.

2.2.4. Study Selection Process

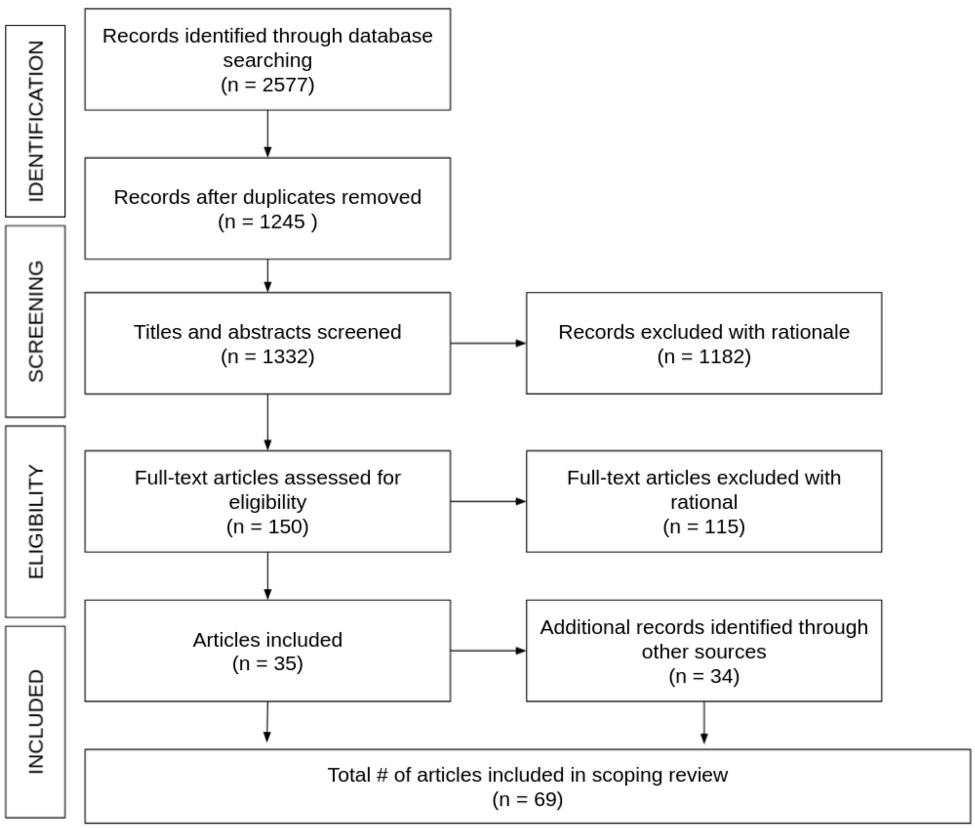
The study screening was conducted using Covidence (systematic review software). Titles and abstracts were screened on pre-specified inclusion and exclusion criteria. Two reviewers (TZ and TQ) independently judged the relevance of the articles, and any disagreements were resolved by a third reviewer (ARP). Before the screening process, the reviewers piloted the selection criteria on 10 randomly sampled articles and discussed their rationales for inclusion or exclusion. This step should have resolved any potential discrepancies in interpreting the scope of the review.

Full-text review was done side-by-side with data extraction and charting. Specifically, one reviewer (TZ) first read the articles in full, extracted, and charted data from the articles voted for inclusion. TZ also looked for relevant studies in the reference lists of the included studies and relevant studies that have cited the included studies. After TZ finished charting all studies, the second reviewer (ARP) then began full-text review votes on Covidence. For any inclusion votes, ARP looked for data charting records from the first reviewer TZ and reviewed the content of the chart. If disagreement on whether or not to include a paper occurs, the two reviewers discussed their rationales until the conflict was resolved.

The electronic database search (both first and second search combined) using PsycINFO ProQuest, PubMed, Web of Science and Scopus, along with the gray literature search using ProQuest Dissertation and Thesis Global and PsyArXiv yielded 2577 articles. After removal of duplicate articles, 1245 remained. Title and abstract screening resulted in 150 articles for full-text review. The reference and PDF management tool Paperpile was used to manage citations and PDFs of papers during full-text review. A cross-referencing of articles that received inclusion votes in the full-text review stage yielded an additional 34, which were directly imported to

Covidence in the full-text review stage. At the end, a total of 69 articles met the eligibility criteria for this scoping review. See **Figure 2.1** for the PRISMA flow diagram.

Figure 2.1: *PRISMA flow diagram for study selection*



2.2.5. Data Charting Process

Extracted data from the included studies was summarized in a data charting table. The original data charting table columns were created as per recommendations of Peters et al. (2019) with regards to the specific information to be extracted. The columns were then refined in the process of charting the first few articles that received inclusion votes in full-text review. Specifically, we adapted the columns to ensure that all key elements specific to sources of individual differences, category learning tasks and strategy use/performance were charted in a succinct and understandable manner. The adaptations were made to ensure that all critical sources of information in relation to the objectives of this scoping review can be extracted. For an article containing multiple relevant studies, we charted the studies that used the same type and modality of categorization task in the same row of the data table; otherwise separate rows were created. If the source of individual differences was predetermined prior to the categorization task and the study compared groups that differed on the source, then sample sizes of the comparison groups were reported; otherwise the total sample size of the study was reported.

Data Items

Key data extracted included sources of individual differences, the ways in which these differences were measured, the type of categorization tasks used, and whether or not categorization performance or strategy usage was different given each source of individual difference. In addition, data were extracted on 1) paper citation; 2) year of publication; 3) country of data collection; 4) aims/objectives; 5) population; 6) sample size (e.g., size of participant group bearing an individual differences character); 7) Age group of participants; 8) baseline tasks to ensure no other differences exist between groups; 9) modality of the categorization tasks; 10) key findings. The data chart is presented in the Supplementary Table (available at : *main data chart*). The specific tasks or instruments used to detect individual differences are reported in the data spreadsheet, and are not reported in the main article.

2.3. Results

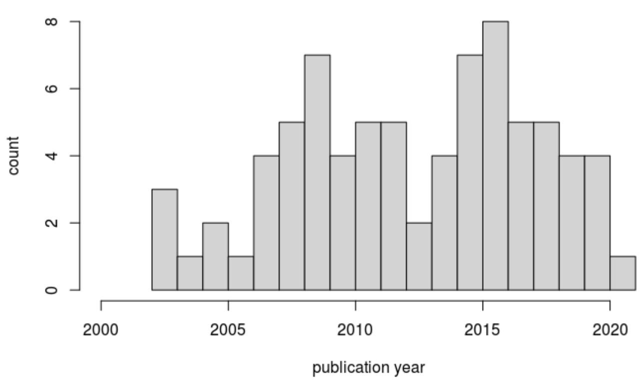
Fifty-four of the 69 articles that met eligibility criteria for the scoping review had their data collected from English-speaking countries (Australia, n = 6; Canada, n = 3; U.K., n = 3; U.S., n = 42). Five included studies' data collection involved multiple countries (China/U.S., n = 1; Japan/China/Korea/U.S., n = 1; Switzerland, Sweden, Germany, n = 1; U.S./Canada, n = 1; U.S./Korea = 1; U.S./Germany, n = 1). The remaining 8 studies' data were collected in Belgium (n = 2), China (n = 2), Germany (n = 2), Hungary (n = 1), Israel (n = 1), the Netherlands (n = 1) and Switzerland (n = 1). Included papers were published between 2002 and 2021, see **Figure 2.2** for the distribution of publication year. Six main themes emerged after careful analysis and synthesis of the 69 included articles: 1) aging, 2) cognition, 3) culture, 4) developmental, 5) expertise, 6) genetics. The proportion of articles belonging to each theme is represented in **Figure 2.3**, along with the frequency counts. Before presenting the detailed results for each theme, it is helpful to provide an overview of the category learning tasks that are relevant to this scoping review. The reader can find the data in chart form in the Supplementary Table (available at: *main data chart*).

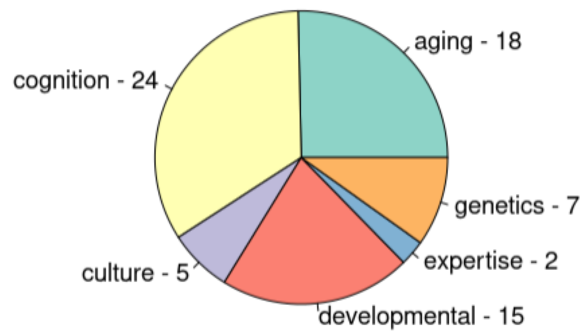
2.3.1. Overview of Category Learning Tasks in the Scoping Review

The categorization tasks included in this review are divided into seven categories: binary features tasks, decision-bound category tasks, probabilistic tasks, triad match-to-sample tasks, relational rule tasks, schema abstraction tasks, and associative patterning tasks. These terms will be used to refer to task structures in the results section. **Binary features tasks** are tasks that use stimuli with binary feature dimensions (or more than 2 discrete values per dimension) stimuli. For example, stimuli can be composed of 3 dimensions (e.g., size, color, shape) and each dimension has 2 values (e.g., size: large, small; color: white, block; shape: triangle, circle). Binary feature tasks can either involve both the training and testing phase (n = 14) or training only (n = 17). Few studies have used testing only (n = 2), and 1 study used test-training-test design. A trial in

Figure 2.2: *The distribution of publication year for articles included in this review.*

Figure 2.3: *Pie chart of uncovered themes with number of articles per theme.*





the training phase has feedback following the response, whereas a trial in the testing phase does not have feedback. The intention behind using a testing phase is often to detect the specific strategy people have been using during the training phase and their strategy preferences. Binary feature tasks with only the training and no testing generally look at overall performance accuracy, learning rate and the number of trials required to reach the criterion (predetermined number of consecutively correct trials).

Decision-bound type of tasks assume that participants learn to associate category space partitioned by the decision bound(s) with particular category responses (Ashby & Gott, 1988; Ashby & Maddox, 1993; Ashby & Townsend, 1986). Stimuli in this type of category are composed of dimensions with continuous values within a predetermined range. Certain decision boundaries are easily verbalizable in relation to stimulus dimensions, resulting in the development of rule-based category structures. Other decision boundaries cannot be easily described in terms of stimulus dimensions, resulting in the development of similarity-based category structures. The majority of studies in this review that used decision bound types of tasks used the training only design (n = 18), and a few used training and testing design (n = 3).

The remaining types of tasks are less represented in studies included in this review. Four articles used **probabilistic tasks** (training only, n = 4), which involve multiple cues and each cue is predetermined to be probabilistically associated with a certain categorical outcome. Participants should implicitly learn the probability of each cue and use the combination of the cues to make categorization decisions. Five studies used **relational rule tasks**, all have the training and testing design. Learning relational rule involves identifying the abstract relation that defines the categories (e.g., if the inner shape or color is the same as the outer shape or color, then category A, otherwise category B), the stimuli in this task are not bounded by any dimension values. **Associative patterning tasks** (training and testing, n = 3) can be learned through discovering the negative rule (A+ and B+ = AB-). A **schema abstraction task** (training and testing, n = 2) presents participants with stimuli that deviate from the category prototype by a certain degree, and examines participants' ability to form a category centered around the prototype. **A triad match-to-sample task** (testing only, n = 1) involves sorting a target stimulus into one of two categories that either shares the deterministic rule feature or overall similarity. Probabilistic and schema abstraction tasks are considered as similarity-based categories, all relevant results are recorded in the corresponding columns of the results tables. Relational rule, associative patterning and triad tasks are considered rule-based tasks, but the rule type in these tasks are distinguished from the unidimensional or multidimensional rule of the binary or decision bound type of tasks. These special rule-based tasks each use a task-specific rule that does not require further differentiation.

Below, we report the results for each theme separately and identify potential gaps in the literature that may be of interest for future exploration. In each theme, we first report the number of articles included to give an overview. Here, an article is referring to a publication with a citation. We acknowledge that multiple studies from an article can be included, and one study may examine several sources of individual difference (e.g., working memory capacity, IQ, and fluid intelligence) or report results from several types of tasks. We report each effect as a study on its own. In other words, the number of studies reported for sources of individual differences or effects on aspects of tasks are not mutually exclusive, one paper may be referred to multiple times in results synthesis. We focus on three aspects of category learning behaviours: learning rate, performance accuracy and strategy use. For each theme, we report how each source of individual difference has been found to relate to each aspect of category learning behaviour (if reported by the study). The type of category learning tasks used in the studies are also reported.

2.3.2. Sources of Individual Differences Identified

Developmental

We identified 15 articles that examined the ways in which children and adults differ in categorization behaviours. Of these, 12 used the visual modality and 3 used the auditory modality. Studies were divided into the following categories based on children participants' ages: preschool children (3-5 years old; n = 10: 8 binary features, 1 decision bound, 1 triad), elementary school children (6-12 years old; n = 16: 7 binary features, 6 decision bound, 1 probabilistic, 2 schema abstraction), and adolescents (13-17 years old; n = 2: 1 binary features, 1 decision bound). The reason for this is to compare studies that had children participants of similar but non-identical age ranges (e.g., one study may have had children between 6 and 8 years of age, while another may have had children between 7 and 9 years of age). All these studies compared one or more children group's category learning behaviour with that of adults.

All of the 8 studies that compared preschoolers and adults' learning behaviour on binary features tasks used a rule-based structure (unidimensional: n = 6; multidimensional: n = 1; rule plus exception: n = 1) and only 3 of these studies adopted a similarity-based structure. The only decision bound task that was used to compare preschoolers and adults had a unidimensional rule-based structure. Among the 7 studies that compared elementary school children and adults using a binary features task, 5 used a rule-based structure (unidimensional: n = 2; multidimensional: n = 2; rule plus exception: n = 1) and 2 used a similarity-based structure. Five studies used a decision bound rule-based task to compare elementary school children and adults (unidimensional: n = 4; multidimensional: n = 1), 2 studies used a decision bound similarity-based structure.

Although all articles in this theme focused on the developmental differences in category learning, 4 studies measured additional individual differences in cognitive capacities: working memory (n = 2; (Rabi et al., 2015; Roark & Holt, 2019) and executive function (n = 2; (Rabi & Minda, 2014b; Reetzke et al., 2016). Rabi et al. and Rabi and Minda showed that working memory capacity did not predict adults' unidimensional rule-based category learning performance but was predictive of children's. On the other hand, Roark and Holt found that working memory capacity was not correlated with children's similarity-based category learning performance, however the modality of their task was auditory whereas Rabi et al. used visual modality. Reetzke et al. showed that Wisconsin Card Sorting Task -- a measure of executive functions, was positively associated with performance.

Table 2.1 and **Table 2.2** present an overview of the results from studies that compared preschool children and adults, and elementary school children and adults, respectively. For citations of specific papers that are referred to by the numbers in the tables, see: *detailed table results*. Most of the studies in **Table 2.1** show that preschoolers tend to have lower performance accuracy than adults and they show a disadvantage in applying a rule consistently on rule-based tasks. On the other hand, fewer studies have looked at preschooler and adult differences in learning similarity-based tasks, the existing results suggest that preschoolers are not different from adults in terms of performance and applying similarity-based strategies[4]. Most of the studies in **Table 2.2** show that elementary school children performed worse in rule-based category learning, both in terms of performance accuracy and consistency with applying the task-appropriate strategy, results were mixed relating to similarity-based category learning. More detailed differences in strategy use between children and adults were also captured. Preschoolers have been shown to prefer similarity-based approaches on both rule-based and similarity-based

[4] Note that we report results from rule-based tasks under rule-based task columns and vice versa for similarity-based tasks. For instance, if one study showed that children were more likely to apply similarity-based strategies on rule-based tasks, this information is recorded under the 'rule-based strategy' column as 'worse' since children were shown to be worse than adults at applying rule-based strategy. Despite that children were shown to be more likely to use similarity-based strategy on a rule-based task, this information was implied and would not explicitly change the numbers in the table.

tasks (Deng & Sloutsky, 2016; Kloos & Sloutsky, 2008; Rabi & Minda, 2014a). On rule-based tasks, preschoolers tended to focus their attention more diffusely on both relevant and irrelevant features (Blanco & Sloutsky, 2019; Yao & Sloutsky, 2010), and they tended to switch strategy more often (Rabi et al., 2015). Similar patterns have been seen in elementary school children. These older children also showed a preference for a similarity-based approach (von Helversen et al., 2010), tended to get distracted by irrelevant features (Kapatsinski et al., 2017), and switched strategies more often (Roark & Holt, 2019). Children's rule applying ability increased with age, Rabi and Minda suggested that by 10 years of age children can reach adult level; Deng and Sloutsky found that 7 year olds' rule-use was more adult-like than children-like in learning rule-based tasks. So it may not be a surprise that (Huang-Pollock et al., 2011) showed that elementary school children (8-12 years old) preferred rule-based strategy in a similarity-based task. Participants in this study have passed the rule-ignorant age, but not yet have the cognitive capacity to determine whether a rule is the optimal solution. This pattern was also seen in older adults (Filoteo & Maddox, 2004; Mata et al., 2011), which was the theme we discussed next. One limitation within the developmental theme was the age group categorization, especially for elementary school children (6 - 12 years old). Children within this age range can vary greatly in their cognitive development and category learning behaviours. However, this was an appropriate age category to be formed considering the age range being studied by included studies and the few number of studies that fall into this category. Future reviews concerning developmental changes may wish to further divide children into more age categories if a large enough number of studies can be included in each age category.

Table 2.1: Relationship between developmental differences and categorization behaviour: comparing preschool children (3 - 5 years old) and adults

	Rule-based task			Similarity-based task		
	Learning rate (n = 2)	Performance (n = 10)	Rule-based Strategy (n = 6)	Learning rate (n = 0)	Performance (n = 2)	Similarity-based Strategy (n = 2)
Children better						
No difference	1 binary	1 binary			1 binary	2 binary
Children worse	1 binary	7 binary 1 d/b 1 triad	5 binary 1 d/b		1 binary	

Note. Each number in the table represents the number of instances within the relevant studies that found a better/null/worse relationship between preschool children (3-5 years old) and adults (either 18-35 years-old or unspecified) for each aspect of category learning behaviour. The bracketed number under each aspect of category learning behaviour shows the total number of instances within the relevant articles that looked at this aspect. Row 3-5 shows the number of studies that used a specific task structure. For succinct representation, we use short forms binary, d/b, relational, triad to represent different category task structures: binary = binary features; d/b = decision bound; relational = relational rule; triad = triad forced choice.

Table 2.2: Relationship between developmental differences and categorization behaviour: comparing elementary school children (6-12 years old) and adults

	Rule-based task			Similarity-based task		
	Learning rate (n = 3)	Performance (n = 11)	Rule-based Strategy (n = 7)	Learning rate (n = 0)	Performance (n = 8)	Similarity-based Strategy (n = 6)
Children better						1 schema abstraction
No difference	2 d/b	1 binary 1 d/b	1 binary 1 d/b		2 binary 1 schema abstraction	2 binary
Children worse	1 d/b	4 binary 5 d/b	1 binary 4 d/b		1 binary 2 d/b 1 schema abstraction 1 probabilistic	2 d/b 1 probabilistic

Note. Each number in the table represents the number of instances within the relevant studies that found a better/null/worse relationship between elementary school children (6-12 years old) and adults (either 18-35 years-old or unspecified) for each aspect of category learning behaviour. The bracketed number under each aspect of category learning behaviour shows the total number of instances within the relevant articles that looked at this aspect. Row 3-5 shows the number of studies that used a specific task structure. For succinct representation, we use short forms binary, d/b to represent the category task structures: binary = binary features; d/b = decision bound.

Normal Aging

There were 17 articles that compared older adults (> 60 years old) and younger adults' (18-35 years old) category learning behaviours. Twenty-five studies from these 17 articles used the visual modality and 2 used the auditory modality. The category learning tasks included in this theme were: binary features (n = 11), decision bound (n = 7), relational rule (n = 2) and probabilistic (n = 2). All of the binary feature tasks used a rule-based task (unidimensional: n = 5; multidimensional: n = 4; rule-plus-exception: n = 2); 6 studies examined similarity-based task learning. Five of the 7 studies that used a decision bound structure examined rule-based learning (unidimensional: n = 3; multidimensional: n = 2); 4 studies examined similarity-based learning.

Age was the main source of individual difference studied across all 27 studies, in addition, 5 studies also measured a variety of cognitive capacities. All 5 studies measured working memory and components of executive functions. Maddox et al. (2010, 2013) and Bharani (2016) only administered cognitive tasks to older adults. The two Maddox et al. studies showed that working memory was positively related to multidimensional rule-based task learning and optimal strategy selection, Bharani et al. found that working memory was not related to unidimensional rule-based learning. Other executive function components were shown to be positively related to both rule-based (Maddox et al. 2010; Bharani et al.) and similarity-based learning (Maddox et al. 2010). Rabi and Minda (2016) found that higher working memory capacity was related to better performance in both multidimensional rule-based learning as well as similarity-based learning when age was controlled; Wahlheim et al. (2016) only found this positive relationship among older adults. Wahlheim et al. also found that among young adults, higher working memory was associated with more similarity-based strategy on the relational rule task, whereas no strategy use can be predicted from working memory among older adults. In addition, Rabi and Minda showed that IQ was not predictive of performance in either younger or older adults. The above results are presented under the 'normal aging 'theme rather than the 'cognitive capacities' theme because aging was the central theme of these studies with cognitive measures being secondary.

Aging-related category learning differences are summarized in **Table 2.3**. The majority of studies found that older adults had worse performance accuracy than younger adults on both rule-based and similarity-based tasks. However, few studies did not find significant performance differences. The results were mixed whether older and younger adults differ in learning rate or strategy use. More detailed differences in strategy use between the two age groups were also captured. When a strategy difference was observed, older adults tended to use more rule-based approaches to learn similarity-based tasks (Filoteo & Maddox, 2004; Mata et al., 2011); they tended to use simple unidimensional rule when a more complex multidimensional rule was required (Glass et al., 2012; Maddox et al., 2013; Merritt et al., 2010); and switch strategy more often than younger adults (Gouravajhala et al., 2020; Rabi & Minda, 2016; Wahlheim et al., 2016).

Table 2.3: Relationship between normal aging and categorization behaviour: comparing older adults and young adults

	Rule-based task			Similarity-based task		
	Learning rate (n = 3)	Performance (n = 18)	Rule-based Strategy (n = 8)	Learning rate (n = 3)	Performance (n = 10)	Similarity-based Strategy (n = 9)
Older adults better				1 binary	1 binary	
No difference	1 binary 1 d/b	4 binary 2 d/b	4 binary 2 d/b		2 binary 1 probabilistic	3 binary 2 d/b 1 probabilistic
Older adults worse	1 binary	7 binary 3 d/b 2 relational	2 binary 1 d/b 1 relational	1 binary 1 d/b	2 binary 3 d/b 1 probabilistic	1 binary 1 d/b 1 probabilistic

Note. Each number in the table represents the number of instances within the relevant studies that found a better/null/worse relationship between older (> 60 years old) and adults (either 18-35 years-old) for each aspect of category learning behaviour. The bracketed number under each aspect of category learning behaviour shows the total number of instances within the relevant articles that looked at this aspect. Row 3-5 shows the number of studies that used a specific task structure. For succinct representation, we use short forms binary, d/b, relational to represent different category task structures: binary = binary features; d/b = decision bound; relational = relational rule.

Cognitive Capacities

There were 22 articles that looked at the ways in which different levels of cognitive capacities can impact people's categorization behaviours. Participants' cognitive capacities were examined: working memory capacity (n = 19), fluid intelligence (n = 4), cognitive reflection (n = 2). Declarative memory, episodic memory, procedural memory, inhibitory control, executive functions (shifting), IQ, local/global processing style, English language ability, verbal/spatial working memory each has been examined by 1 study. The category learning tasks in this theme were: binary features (n = 11), decision bound (n = 11), associative patterning (n = 4), relational rule (n = 7), schema abstraction (n = 1) and triad (n = 1). Out of the 11 binary features tasks, 10 included a rule-based task (unidimensional rule: n = 3; multidimensional rule: n = 3; rule-plus-exception: n = 4) and 5 included a similarity-based task. Out of the 11 decision bound tasks, 6 included a rule-based task (unidimensional rule: n = 6) and 11 included a similarity-based task.

Table 2.4 shows an overview of study results on the relationship between working memory capacity and category learning behaviours. Some of the studies addressed in the table have also found more specific relationships between working memory capacity and strategy patterns. Three studies found that lower working memory capacity was associated with simple rule use in learning similarity-based tasks (Carlson, 2009; DeCaro et al., 2009; McHaney et al., 2021), Decaro et al. and Carlson also found that high working memory capacity was related to more optimal strategy use regardless of the type of task. All studies addressed in the table used one or more versions of the span task to measure working memory capacity. The table results show that higher working memory capacity tended to be associated with faster learning rate and better performance on similarity-based tasks, results were mixed with regards to rule-based task performance. Moreover, working memory did not consistently predict strategy use. More studies that used rule-based tasks found no relationship between working memory capacity and rule-use than studies that found a positive relationship. Higher working memory capacity tended to predict optimal strategy use in similarity-based tasks, but this relationship may be less robust given the small number difference between the studies that found this pattern and the studies that did not find a relationship.

Results relating to other cognitive factors were reported only in the main text rather than separate tables. We discuss rule-based category learning results first. Fluid intelligence (Little & McDaniel, 2015; Maes et al., 2017) and executive functions shifting component (Wang et al., 2015) have been shown to be positively related to learning rate, inhibitory control was found to be negatively related to learning rate (Ryherd, 2019). English language abilities (Ryherd, 2019), fluid intelligence (Goldwater et al., 2018) and verbal working memory (Carlson, 2009) were found to predict performance accuracy in the positive direction, cognitive reflection (Goldwater et al., 2018) and IQ (Iwashita, 2020) did not predict performance. Higher cognitive reflection (Don et al., 2016) and fluid intelligence (McDaniel et al., 2014) has been shown to be associated with more rule-based strategy use, but another study on cognitive reflection showed no relationship with strategy use (Goldwater et al., 2018). Don et al. used an associative patterning task, whereas Goldwater et al. used a relational rule task. Fluid intelligence (Goldwater et al., 2018; Little & McDaniel, 2015; Maes et al., 2017), local/global processing style (Maes et al., 2017) and executive function shifting component (Wang et al., 2015) did not predict strategy use.

Table 2.4: Relationship between working memory capacity and categorization behaviour

	Rule-based task			Similarity-based task		
	Learning rate (n = 5)	Performance (n = 9)	Rule-based Strategy (n = 11)	Learning rate (n = 5)	Performance (n = 5)	Similarity-based Strategy (n = 7)
Higher WM better	3 binary 2 relational	4 binary 1 d/b	1 binary 1 d/b 1 associative patterning 1 relational	2 binary 1 d/b	1 binary 4 d/b	2 binary 2 d/b 1 schema abstraction
No difference		1 binary 2 d/b 1 relational	3 binary 2 d/b 2 relational	1 d/b		2 d/b
Lower WM better				1 binary		

Note. Each number in the table represents the number of instances within the relevant studies that found a positive/null/negative relationship between working memory capacity and each aspect of category learning behaviour. The bracketed number under each aspect of category learning behaviour shows the total number of instances within the relevant articles that looked at this aspect. Row 3-5 shows the number of studies that used a specific task structure. For succinct representation, we use short forms binary, d/b, relational to represent different category task structures: binary = binary features; d/b = decision bound; relational = relational rule.

Next, we discuss results from similarity-based category learning tasks. None of these studies we reviewed found a relationship between variations in cognitive capacities and learning rate. Episodic memory (Hoffmann et al., 2014) and spatial working memory (Carlson, 2009) were shown to positively relate to performance accuracy, while English language abilities negatively predicted performance accuracy (Ryherd, 2019). Declarative, procedural (Quam et al., 2018) and episodic memory (Hoffmann et al., 2014) was shown to positively associate with more similarity-based strategy use. The majority of studies that examined cognitive capacity differences used visual stimuli, but (Quam et al., 2018) used an auditory similarity-based category and (McHaney et al., 2021) used a similarity-based speech category which was also delivered through auditory modality. If the reader wishes to see the specific tasks that were used to measure the individual differences, refer to: main data chart[5].

[5] The tasks in the data chart are listed as index numbers from the 'task index metadata' tab in the same Google Sheet. Task index metadata is a list of all tasks that were used to measure individual differences in the articles included in this scoping review, along with the purpose of each task and its citation.

Culture

Four articles examined the ways in which culture may affect people's category learning behaviour, all these studies compared Eastern (East Asia) and Western (U.S.) culture. Because the studies included in this section were few and showed mixed results, we discuss each study separately without synthesizing results from all studies. Norenzayan et al. (2002) study 1 (binary features) found that European and Asian Americans applied the rule better than East Asian when the rule was explicitly described to them. However, all cultural groups learned similarly when no rule was taught. Study 2 of Norenzayan et al. found that European Americans tended to use more rule-based approaches and were less flexible to task demands. Cagigas (2008) found that Asians, Latinos and Caucasian Americans performed similarly on unidimensional rule-based and similarity-based tasks, but Caucasians were better at learning the conjunctive rule. Klein et al. (2009) found no performance or strategy use difference between Japanese, Koreans, Chinese and Americans. Murphy et al. (2017) found that Americans were more likely to use similarity-based strategy than Koreans when neutral task instruction was given, and the two cultural groups did not differ in strategy use when task instruction prompting similarity-based approach was given.

Norenzayan et al (2002) and Cagigas (2008) suggested that Caucasian Americans had an advantage applying rule-based strategies. Murphy et al. (2017), on the other hand, showed that Caucasians were more biased towards similarity-based approaches. Norenzayan et al. and Murphy et al. also found contradicting effects of task instruction. The former showed task instruction brought out the cultural differences, whereas the latter showed that cultural differences were removed after explicit task instruction. The overall picture from these 4 studies created a mixed picture with regard to the cultural effect and there may be too little evidence to draw any firm conclusions.

Genetics

Six articles were included in the theme of genetic effects on category learning behaviours. Skilleter et al. (2014) examined how brain derived neurotrophic factor (BDNF) Val66Met polymorphism (2 genotypes: val homozygotes and met-carriers) and the risk for developing schizophrenia influence probabilistic category learning. The authors found that met-carriers with lower schizotypal scores had better performance than met-carriers with higher schizotypal scores and val homozygotes with high or low schizotypal scores. They further found that lower schizotypal scores tended to be associated with optimal multi-cue strategy.

Chandrasekaran et al. (2015) studied the polymorphism of forkhead box protein P2 (FOXP2; 3 genotypes: AA, AG, GG) and success in non-native speech category (similarity-based decision bound) learning. Results showed that the GG genotype was associated with enhanced speech category performance, and more optimal similarity-based strategy use compared to A homozygotes.

Maddox et al. (2015) examined the influence of serotonin transporter gene (5-HTTLRP) polymorphism (3 genotypes: S'S', L'S', L'L') on participants' ability to choose task appropriate category learning strategy (binary feature). They found that the S'S' genotype had an advantage learning binary features, similarity-based categories, and the L'L' genotype had an advantage learning binary features, rule-based categories.

Xie et al. (2015) looked at dopamine receptor D2 (DRD2) polymorphism C957T (3 genotypes: TT, CT, CC) and rule-based and similarity-based category learning in both visual and auditory modalities (binary feature). The researchers found that in the visual domain, TT homozygotes were faster at learning the binary features, similarity-based task than C-carriers, but no difference across genotypes in learning the rule-based task. Similarly, in the auditory domain, TT homozygotes learned the binary features, similarity-based task faster than C-carriers, and C-carriers were faster at learning the rule-based task than TT homozygotes.

Byrne et al. (2016) assessed the role of multiple dopaminergic genes polymorphism (DRD2, DARPP-32, and COMT - Val158Met) on performance in two rule-based category learning tasks (decision bound). DARPA-32 polymorphism has 3 genotypes: GG, GA, AA. COMT polymorphism has 3 genotypes: Val-Val, Val-Met, Met-Met. Results showed that DRD2 TT homozygotes outperformed C-carriers on both unidimensional and conjunctive rule-based tasks; the same superior performance was also found for DARPP-32 AA homozygotes when compared with G-carriers. Moreover, the COMP Met allele predicted superior performance on the conjunctive rule-based task.

Schuck et al. (2018) tested whether age-related probabilistic category learning behavioural differences are related to the KIBRA gene (3 genotypes: CC, CT, TT) which was found to be related to hippocampal function. It was found that when learning from feedback, T-allele was positively associated with learning in older adults, but when learning from observation, CC homozygotes achieved better performance. On the other hand, young adults' performance was not affected by KIBRA polymorphism.

Taken together, each study examined different gene(s) and associated certain category learning advantages with specific genotypes. Only one gene polymorphism was investigated by more than one study - DRD2 (TT, TC, CC). Xie et al. (2015) showed that C-carriers had an advantage learning rule-based tasks. However, Byrne et al (2016) found the opposite results – TT homozygotes were actually the ones possessing this advantage. These contradictory results may be due to task differences. Xie et al. used binary dimension tasks while Byrne et al. used decision bound tasks. Despite the task variations, one would still have expected the genetic effect to be carried across tasks. This shows that additional research is much needed before we can conclude about the robustness of any genetic effects.

Remaining Articles

There were collectively 5 remaining articles to be covered in this scoping review, these can be divided into 4 additional topics: expertise (n = 2), stress (n = 1), iron deficiency (n = 1) and personality (n = 1). The 2 articles on expertise looked at music experience (Roark et al., 2020) and action video gaming experience (Schenk et al., 2020). Roark et al. used decision bound tasks and found that musicians were more likely to use the optimal strategy and perform better than non-musicians at the auditory rule-based task, only when the rule was explicitly described to the participants. Musicians and non-musicians' categorization behaviors did not differ in visual rule-based, similarity-based tasks, as well as the auditory similarity-based task. Schenk et al. (binary feature) showed that video-action gamers were better at learning tasks with a rule-plus-exception structure.

Ell et al. (2011) examined the effect of threat appraisal (stress) and found that higher threat appraisal was associated with enhanced accuracy on the similarity-based task and impaired performance on the rule-based task (decision bound). The more stressed participants were, the more they used task appropriate strategy on the similarity-based task.

One study in our review examined blood-iron level and its effect on decision bound categorization. Rhoten (2018) found that iron deficient participants performed worse on the rule-based task than the control group, but the two groups did not differ in strategy use. On the other hand, the two groups did not differ on similarity-based task performance despite that the iron deficient group were less likely to learn the optimal similarity-based strategy than the control group.

Tharp (2007) looked at how factors related to personality can affect category learning behaviours, four studies within this dissertation article were included in this review. Two studies used binary feature tasks, one found that Neuroticism was negatively associated with both rule-based and similarity-based category learning performance but no relationship between personality factors and strategy use, the other study found that none of the personality factors was related to category learning performance. The rest of the two studies used decision bound types of categories (conjunctive rule). One study showed that impulsive, anti-social, sensation seeking components of personality were negatively related to performance and positively related to suboptimal rule-based strategy use. Extraversion was positively related to more optimal rule-based strategy use. On the contrary, the last study found that optimal rule-based strategy users tended to have higher scores on the impulsive, anti-social, sensation seeking components and Neuroticism levels than suboptimal strategy users, contradicting findings from other studies within the same dissertation. This study also found that higher extraversion was associated with more optimal strategy use, corresponding to other study's results. As we can see, results can be contradictory even within the same study when different category learning tasks (e.g., binary feature vs. decision bound) were used, suggesting that additional evidence is needed to draw conclusion. Since only isolated studies covered the topics in this section, no further result synthesis was done.

2.4. Discussion

The 69 articles reviewed contribute new knowledge to the field of category learning and cognition, by providing an overview of the various sources of individual differences that have been examined in relation to category learning behaviours. While the studies differed in task selection, source of individual differences and the focus of specific aspects of category learning behaviours, 9 clear themes emerged. The implications of the finding from this scoping review are discussed below.

2.4.1. Summary of Findings

Despite the included articles covering a broad range of themes, only 3 themes were well investigated - developmental, aging and cognitive capacities. Within the developmental theme, results were synthesized separately for preschool children and elementary school children. The majority of studies found that both children groups showed lower performance accuracy on rule-based tasks compared to young adults, and this pattern was observed in a variety of category learning tasks (e.g., binary, decision bound). Results relating to similarity-based tasks were more mixed. The two groups differed in their strategic preferences in different type of tasks, preschoolers tended to be rule-ignorant and approach any type of task with similarity-based approach, and by 7-10 years of age children started to form rule-based knowledge and applied it to learning tasks (Deng & Sloutsky, 2016; Rabi & Minda, 2014a). However, older children still displayed disadvantages in rule-based tasks due to getting distracted by irrelevant features of task stimuli (Kapatsinski et al., 2017) and an inability to consistently apply the optimal rule (Roark & Holt, 2019). Older adults showed a similar performance deficit as children in both rule-based and similarity-based category learning tasks, but the results were mixed with regards to whether or not there was a disadvantage in strategy use. Studies that did find differences in strategy use suggested that older adults were more likely to use rule-based strategy to learn similarity-based tasks (Filoteo & Maddox, 2004; Mata et al., 2011), use simple rules when a complex rule was required (Glass et al., 2012; Maddox et al., 2013; Merritt et al., 2010), and switch strategy more often than young adults (Gouravajhala et al., 2020; Rabi & Minda, 2016; Wahlheim et al., 2016). Taken together, these age-related studies showed that older children and older adults prefer simple rules, while younger children prefer similarity-based approaches in all types of tasks. To counteract these tendencies, the underlying category structure should be made explicit to these age groups so that they do not persist on using the suboptimal approach.

A variety of cognitive factors have been investigated by studies included in this scoping review, with working memory capacity being the most studied topic. Results have generally agreed that higher working memory capacity was associated with better performance accuracy and faster learning rate on similarity-based tasks, but results were mixed with regards to rule-based tasks. Moreover, higher working memory did not seem to affect people's strategy use on rule-based tasks, and mixed results were shown for similarity-based tasks. Some studies have shown that lower working memory capacity was associated with simple rule use in similarity-based tasks (Carlson, 2009; DeCaro et al., 2009; McHaney et al., 2021), and less optimal strategy use (Carlson, 2009; DeCaro et al., 2009; McHaney et al., 2021). The relationships between other cognitive variables and category learning behaviours were investigated by few studies, no general patterns can be extracted.

The studies that examined the remaining themes showed that while genetic variation was generally a valid source of individual differences that causes category learning differences, comparing East and West culture did not yield robust behavioural differences. Recent studies that looked at expertise (music, gaming) showed some aspects of category learning differences, but more studies using different types of tasks are needed to replicate these results. The studies on threat-appraisal, blood iron level and personality each formed its own theme and all found interesting results. Further investigation is in demand in these areas to uncover more solid relationships.

2.4.2. Limitations and Methodological Issues

The primary objective of our scoping review was to explore what sources of stable individual differences can affect people's category learning behaviours, and in what way. We only included studies that were written in English, however, we do not expect this to lead to a selection bias because the included studies showed that cultural exposure did not consistently affect people's category learning behaviours. In addition, our criterion that only experiments and quasi-experiments be included resulted in the exclusion of narrative reviews on this topic. Another limitation is the way we categorized the age groups in the developmental theme, the age of the elementary school children group (6-12 years old) spans several developmental stages and these participants may differ in category learning behaviours. We chose this range after examining the age groups studied by the included studies as well as the total number of studies that focus on each age group. Further dividing the age groups would result in too few studies for results synthesis. Lastly, careful readers may have noticed that nearly as many included articles were found using the supplemental approach as were the initially identified articles in the systematic search. The formal search essentially missed half of the relevant articles. This is not necessarily a limitation of this review as much as of the formal systematic article selection process. It may require additional scrutiny on the part of the researcher to ensure as many relevant articles can be discovered as possible. Despite these minor limitations, our scoping review is the first that systematically examines the factors behind differential category learning behaviours.

2.4.3. Conclusions

Categorization is a fundamental skill that is required in all aspects of life, and categories or concepts are the building blocks of the knowledge we have about the world. Therefore, understanding what factors facilitate or impair category learning is the critical first step to effectively creating and transferring knowledge. Factors such as age, cognitive capacities, genetic variations have been shown to influence category learning behaviours. Children, older adults, individuals with lower cognitive capacities and certain genotypes may require additional training or explicit learning instructions to fully grasp the nature of the task in order to achieve optimal learning. The rest of the themes identified in this scoping review have been sparsely studied, future research may be interested in extending on these available results.

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3. Chapter 3-Temperament Traits Have Minimal Effect on Category Learning

Transient affective states have been shown to affect cognition, including category learning, but less is known about the role of stable temperament traits and categorization. In two studies, I examined affective temperament traits to see whether the tendency to experience negative and positive affect is predictive of category learning performance and strategy use. Temperamental effortful control and working memory were measured as covariates. In both studies, participants first completed the Adult Temperament Questionnaire (Evans & Rothbart, 2007) including two affective temperament traits and trait temperamental effortful control. Then they completed a memory task followed by either a conjunctive rule-based (CR) or an information integration (II) category learning task. Results suggest that affective temperament traits may have little to no effect on either type of category learning. Temperamental effortful control may be associated with lower overall performance on both types of category learning, and working memory may be associated with higher overall performance on both types of category learning, but these findings were not consistent across studies. These results extend prior literature and provide additional insights on the effects of stable temperament traits and working memory on category learning.

Keywords: *temperament, personality, category learning, working memory*

3.1. Introduction

3.1.1. Individual Differences in Category Learning

Categorization is the cognitive ability which allows us to efficiently manage the knowledge we have about the world. Many cognitive theories have attempted to understand the underlying mechanisms of category learning (Ashby et al., 1998; Medin & Schaffer, 1978; Minda & Smith, 2001; Nosofsky, 2015; Rosch, 1973).

COVIS (COmpetition between Verbal and Implicit Systems) is a category learning model that assumes people learn categories through either an explicit rule-based system or an implicit similarity-based system depending on the category structure (Ashby et al., 1998; Ashby & Valentin, 2017; Davis et al., 2012). Much of the evidence for the COVIS theory came from research examining the acquisition of rule-based and similarity-based tasks. In rule-based tasks, the optimal strategy is one that can be explicitly described by a verbalizable rule (Ashby et al., 1998). For example, an adult is considered to be of a healthy weight when their BMI falls between 18.5 and 24.9, any BMI outside of this range would be considered unhealthy. In similarity-based tasks, the optimal strategy would be difficult or impossible to describe verbally. It generally requires simultaneous perceptual integration of several incommensurable stimulus features at a pre-decisional stage. For example, distinguishing a curious wild coyote from pet dogs at an off-leash dog park.

There has been substantial evidence that individuals can differ in their strategic approach in learning the same categorization task (Ashby et al., 1998; Meeter et al., 2006; Nosofsky & Zaki, 2002; Pelley et al., 2019; Raijmakers et al., 2001). Studies have shown that individuals do not always apply the task-appropriate optimal strategy. Rule-based strategies were seen to be used in similarity-based tasks and vice versa for similarity-based tasks, despite the subpar performance (Donkin et al., 2015; Minda & Smith, 2001; Wills et al., 2015). It is not clear why people adopt different strategies and what trait variables might predict strategy selection. As seen in Chapter 2, the scoping review did not identify a clear predictor of individual differences in category learning strategy use. In this series of experiments, I sought to examine whether temperament traits contribute to individual differences in category learning strategy use. Specifically, whether individuals with certain temperament traits show an advantage in learning the optimal strategy prescribed in either a rule-based or a similarity-based categorization task. In the next sections, I first introduce the temperament traits and then provide theoretical rationales as to why these traits have strong potential to be associated with strategy preferences.

3.1.2. Temperament

Temperament is thought to be composed of two dimensions: emotional reactivity and emotional regulation (Chess et al., 1960; Goldsmith et al., 1987; Rothbart et al., 1994). Evans and Rothbart (2007) developed the Adult Temperament Questionnaire (ATQ) that measures four temperament traits: negative affect, extraversion/surgency, effortful control, and orienting sensitivity. I restricted my interest only to the first three traits which are considered relevant.

Orienting sensitivity was not examined in the present series of experiments. This trait concerns the tendency to detect subtle external sensory events and spontaneous internal contents. Although individuals with higher perceptual sensitivity may perceive unique category stimuli as more different than people who are lower on this trait, this would apply both to within category stimuli and between category stimuli. Therefore, despite people with higher orienting sensitivity may be equipped with magnifying glasses, the overall category learning experience should not differ based on this trait. Moreover, no prior studies have suggested constructs relating to orienting sensitivity are linked to category learning strategy use.

The negative affect and extraversion/surgency falls in the emotional reactivity component, while effortful control encompasses the emotional regulation component.

Affective Temperament - Emotional Reactivity

The negative affect and extraversion/surgency traits are related to emotional reactivity and refer to the tendency to experience frequent, intense and prolonged negative or positive emotional arousal, respectively (Rothbart & Bates, 2007). Although most of the research attention on emotional reactivity has been about negative affect, individuals also differ greatly on their reactivity of positive emotions (Spinrad et al., 2004).

Studies have uncovered structural and functional correlates of affective temperament traits. Much of this evidence suggests that individuals with certain affective temperament traits (e.g., high trait negative affect) show higher resting state activities in relevant brain regions in much the same way as during elicited transient affect (e.g., negative affect; see Whittle et al., 2006 for a review). Transient negative affect has been shown to be associated with increased amygdala activation, both when participants were exposed to aversive stimuli (Zald, 2003) and asked to maintain negative mood (Davidson et al., 1999; Schaefer et al., 2002). Amygdala activation was seen during resting state in individuals who self-rated high on trait negative affect (Davidson & Henriques, 2000). Similarly, patients with anxiety related disorders who experience chronic negative affect consistently show increased amygdala activation during resting state (Drevets, 1999). Liotti et al. (2000) showed that transient negative affect was correlated with decreased activation of the right dorsal-lateral prefrontal cortex in the healthy population. This reduction in activity and volume was similarly seen in patients who suffer from chronic negative mood symptoms (Drevets, 1999). Harmon-Jones and Allen (1997) found increased activity in the left dorsal-lateral prefrontal cortex to correlate with trait positive affect. The anterior cingulate cortex (ACC) is the core brain region involved in reward-related dopaminergic systems, the functions of dorsal ACC are related to motivation and positive affect (Allman et al., 2001). Previous research has shown that lesions or reduced activity of the dorsal ACC are related to the lack of pleasure and motivation in psychiatric patients with chronic negative affect (Sigmundsson et al., 2001). On the other hand, activity in the ACC is found to be related to trait positive affect (Whittle et al., 2006). The above evidence demonstrated the overlaps between episodes of emotional reactivity and affective temperament traits.

Effortful Control - Emotional Regulation

Effortful control is an attention-related ability which allows people to focus and shift attention to desired channels (Rothbart & Bates, 2007). Posner and Rothbart have argued that the same brain regions (lateral prefrontal cortex, and anterior cingulate cortex) related to the executive attention network also support effortful control (Posner et al., 2007; Posner & Rothbart, 2007). Whittle et al. (2008, 2009) also indicated that individual differences in effortful control are related to the structural and functional variations in the neural substrate corresponding to the executive attention network. Welch (2001) noted that the functions associated with executive attention tend to overlap with the components of executive functions, including attention shifting, working memory updating, and dominant response inhibition.

Posner and colleagues (Posner et al., 2007; Posner & Rothbart, 2007) suggest that the neurocognitive network underlying effortful control becomes activated in situations requiring detection and correction of errors, or overcoming habitual or automatic responses. Individuals' with higher effortful control tend to perform more efficiently on cognitive tasks involving visual or spatial conflicts (i.e., Stroop, flanker or Simon; (Rothbart & Bates, 2007)). Effortful control has been shown to modulate the effects of emotional reactivity. People with high negative affect are less likely to display problems when they have high effortful control (Rothbart & Bates, 2007; Rothbart & Posner, 2006). In line with this, Drevets and Raichle (1998) showed that when effortful control is strengthened, the affective activities tend to be reduced. These results demonstrated the role of effortful control in the modulation of emotional reactivity.

3.1.3. Temperament and Category Learning

3.1.3.1. Affective Temperament and Category Learning

Dopaminergic Theory

Ashby and colleagues (Ashby et al., 1998, 1999) suggest that positive affect facilitates both explicit rule-based learning and implicit similarity-based learning. These researchers proposed the dopaminergic theory of positive affect, which argues that the effects of positive affect on cognition are mediated by dopamine. It also assumes that an increase of dopamine release in the anterior cingulate cortex and prefrontal cortex during transient positive mood states increases cognitive flexibility and verbal fluency. Cognitive flexibility and verbal fluency are related to rule selection and rule switching (Owen et al., 1993), which are beneficial to rule-based category learning. The dopaminergic theory further postulates that striatal dopamine is critical in mediating feedback in procedural learning (Ashby et al., 2007). Positive affect facilitates similarity-based tasks through projecting dopamine into the striatum, a critical region involved in this type of processing. Moreover, higher cognitive flexibility may also speed up the process of exhausting potential rule-based strategy before resorting to the similarity-based strategy. Based on the dopaminergic theory, positive affect should facilitate both rule-based and similarity-based category learning, while negative affect should not affect these learning processes.

Empirical evidence has supported the dopaminergic theory on its assumption that positive mood facilitates rule-based category learning, but results were less consistent with regard to similarity-based category learning. Nadler et al. (2010) found that positive mood facilitated optimal strategy discovery on both rule-based and similarity-based category learning tasks, but significant performance difference between mood states was only observed in the rule-based task. (Nielsen & Minda, 2018) found positive mood significantly facilitated learning on the rule-based categorization task, but they did not find any mood effects on learning of the similarity-based task.

The dopaminergic theory holds a prominent position within the category learning literature. However, much of the research on mood, affect, and cognition falls in the realm of social psychology. Accordingly, I reviewed the social psychology literature for additional insights of the affect and cognition relationship.

Affect-as-Information Framework

One prominent theory originated from social psychology that tries to explain the association between affect and processing style is the affect-as-information hypothesis. This theory proposes that people rely on their mood to guide judgment, decision-making and information processing (Clore, 1992; Schwarz & Clore, 1983). Positive affect signifies a safe environment and promotes a focus on internally accessible information, and negative affect signifies problematic environment and promotes a focus on gathering external information (Clore et al., 2001). Internally focused approaches tend to be intuitive and implicit, while externally focused approaches tend to be analytical and explicit. Gasper and Clore (1998) found that people high in trait negative affect have difficulty parsing out their emotional feelings from information processing. It can be speculated that these individuals are chronically in the mode of vigilance and analysis. Several studies have shown that negative affect, such as anxiety and stress can trigger an effortful, analytical processing style (Clark & Isen, 1982; Isen, 1987). Studies on positive mood and cognition are also abundant and findings indicate that people in a good mood tend to reach decisions more quickly, use less information, and avoid analytical thinking (Ashby et al., 1999; Bless et al., 2006; Fiedler, 2001; Fredrickson, 2009; Hertel & Fiedler, 1994; Isen & Daubman, 1984). Moreover, implicit holistic processing has been shown to make people happier than local processing (Akbari Chermahini & Hommel, 2012; Ji et al., 2019). Therefore, the relationship between affect and processing style is bi-directional and consistent. According to the affect-as-information framework, positive mood promotes implicit processing which benefits similarity-based category learning, and negative mood promotes explicit processing which benefits rule-based category learning.

Hypotheses of Affective Temperament and its Effect on Category Learning

I have demonstrated in an earlier section the overlaps between episodes of emotional reactivity and affective temperament traits. Therefore, it is reasonable to formulate hypotheses based on theories of mood states, in the absence of a more direct theoretical account.

If the dopaminergic theory holds true, I predict that higher extraversion/surgency will be associated with an advantage in learning both rule-based and similarity-based categories. People with these traits should show a greater tendency to use the task-appropriate strategy, regardless of the task. On the other hand, if the affect-as-information framework was true, higher extraversion/surgency and lower negative affect should only be associated with better learning on the similarity-based task. People with these traits should show a tendency to engage in implicit and less effortful processing, corresponding to the optimal approach of similarity-based tasks. Affect-as-information framework also proposes that people with lower extraversion/surgency and higher negative affect should have an advantage in learning the rule-based categories. These traits should be linked to the tendency to engage in explicit analytical processing, corresponding to the optimal approach of rule-based tasks.

3.1.3.2. Effortful Control and Category Learning

Executive Attention and Effortful Control

Temperament is relatively stable, but it may not fully stabilize until preschool years due to the later emergence of effortful control (Rothbart et al., 2003). This can be attributed to the brain's development of the executive attention system (Rothbart et al., 1994; Rueda, 2012) which coincides with children's ability to apply explicit rule-based strategies in category learning (Deng & Sloutsky, 2016; Rabi & Minda, 2014). In addition, neuroimaging data (Konishi et al., 1999; Lombardi et al., 1999; Rao et al., 1997; Rogers et al., 2000) has shown that structures in the executive attention network (i.e., prefrontal cortex, caudate nucleus and anterior cingulate) were activated during rule use in tasks like the Wisconsin Card Sorting Task.

The COVIS assumes that a rule-based category is best learned through explicit hypothesis-testing, which requires heavy involvement of executive attention (Ashby et al., 1998, 1999). Specifically, the participant needs to attend to a certain feature of the stimuli to test its validity as the optimal rule, at the same time not getting distracted by irrelevant features. If the tested rule was incorrect, the participant needs to shift attention to a new feature and conduct hypothesis-testing again. Research on both children and adults has consistently shown that individuals with underdeveloped or overburdened executive attention tend to underperform on rule-based category learning tasks (Deng & Sloutsky, 2016; Miles & Minda, 2009; Davidson et al., 2003; Filoteo et al., 2010; May & Hasher, 1998; Wang et al., 2015; West, 1999; Williams et al., 1999; Deng & Sloutsky, 2016; Miles & Minda, 2009).

As discussed earlier, the optimal approach to learn the similarity-based category is through implicit holistic processing. It has been suggested that higher executive attention is facilitative in this type of learning as well (Ashby et al., 1998). Specifically, the default approach people tend to use is one that is rule-based, therefore, higher executive attention facilitates the exhaustion of potential rules so the learner can swiftly switch to an implicit approach.

Hypotheses of Temperamental Effortful Control and Category Learning

Overall, higher executive attention is linked to better rule-based and similarity-based category learning through faster discovery of the task appropriate strategy. These findings can be applied to temperamental effortful control based on the same underlying mechanisms. Individuals with higher effortful control should also have an advantage in learning either type of the category learning task. Moreover, effortful control was shown to regulate emotional reactivity and inhibit dominant and automatic responses. It should modulate response biases associated with affective temperament to further facilitate optimal strategy learning.

The present chapter introduces two experiments that investigated the relationship between temperament traits and category learning strategy use. In Experiment 1, I used category learning stimuli that vary on two continuous dimensions. In Experiment 2, I used category learning stimuli that vary on two binary dimensions.

3.2. Experiment 1

The rule-based task used in Experiment 1 had a conjunctive rule (CR) category structure and the similarity-based task had an information-integration (II) category structure. The CR structure was comparable to II structure because optimal learning on both tasks would require paying attention to two different stimuli dimensions. The CR and II tasks each relied on a decision bound design which allows for strategy detection (Ashby & Gott, 1988; Soto & Ashby, 2015). The strategy analysis in this design assumes that participants' category learning strategies can be modeled by one or more linear decision boundaries that pass through stimulus space. A variety of decision bound models are fitted to each participant's responses and the best fitting one is selected to represent the strategy used by the participant (Ashby & Todd Maddox, 2005, 2011; Ashby & Valentin, 2017). These modeling procedures would make it possible to distinguish the rule-users from the ones that tend to rely on similarity-based processing in either the CR and II task. Therefore, the decision bound design is an excellent choice in the present research which determines the temperament and category learning strategy relationship. On top of strategy analysis, performance on the task is another indicator of people's strategy use. It has been shown that higher performance can be achieved through the optimal strategy compared to suboptimal ones (Ashby & Maddox; Ashby & Valentin).

3.2.1. Methods

Materials

Adult Temperament Questionnaire. (ATQ; Evans & Rothbart, 2007) includes 77 items which measure three temperament subscales from extremely untrue (1 out of 7) to extremely true (7 out of 7) on 7-point Likert scales. The subscales used in the current study were *Negative Affect* (e.g., It doesn't take very much to make me feel frustrated or irritated), *Extraversion/Surgency* (e.g., It doesn't take much to evoke a happy response in me), and *Effortful control* (e.g., I can keep performing a task even when I would rather not do it). It has been shown that ATQ subscales are closely related to factors within the Big Five adult personality framework. Specifically, Negative Affect, Extraversion/Surgency and Effortful Control map onto personality traits Neuroticism, Extraversion and Conscientiousness dimensions of the Big Five adult personality (Ahadi & Rothbart, 1994; Evans & Rothbart, 2007; Rothbart et al., 2000). This questionnaire was hosted on Western University's Qualtrics (https://mysurveys.uwo.ca/). At the end of the ATQ, the participants were given a clickable link that directed them to complete the next two tasks.

Reading Span Task. (RSpan; Daneman & Carpenter, 1980). This working memory task was originally designed by Daneman and Carpenter (1980). The current task was hosted on Pavlovia (Peirce, 2007), a platform that allows you to export locally-developed PsychoPy experiments online for easy data collection from many remote recruitment sources. On each trial, the participants read a sentence and they had to judge the meaningfulness of the sentence and also memorize the last word of the sentence for later serial recall. Each sentence appeared centrally on the screen, along with the text instruction -- “Meaningful - press A”, “Not Meaningful - press B” at bottom left and right, respectively. There were equal numbers of meaningful (e.g., “She knows many witty people”) and meaningless (e.g., “Fish cut their nails after lunch”) sentences. Participants had maximum 4.5s to respond before the next trial began. They were informed that performance accuracy less than 80% on the meaningfulness judgment will not be included in the analysis. Although participants did not receive feedback on the meaningfulness judgment, their responses were recorded to assess potential sentence processing and memorization trade off (Robert et al., 2009). The trial sequence repeated two to six times depending on the set size. The intertrial interval was 500ms; and the order of set size was pseudorandomized, which means large set sizes can appear earlier than smaller set sizes. Following the set presentation, recall of the final words was prompted with “Please recall now” and a blank response box for typing. The participants typed as many words as they could recall from the current set. They were informed that the order of the words did not matter. There was no timing constraint for recall, participants clicked a radio-button after they finished typing. Feedback on recall was provided in the form of “You got X out of N correct!” (displayed for 1s).

There were altogether 60 sentences or 15 sets, the set size ranged from 2 to 6, each set size appeared three times. The sentences used in this task were selected from the sentence stimuli of Lewandowsky et al. (2010), sent through email correspondence from Dr. Klaus Oberauer (personal communication, December 2020). All of the sentences contained between 3 and 6 words. All final words contained between 3 and 6 letters, and had 1 or 2 syllables. Practice trials were provided before the actual task, the participants first learned the meaningfulness judgment part through four trials, then learned the memorization part through another four trials, and finally they practiced one set of size 4 that followed the procedures of the actual task. Participants continued to the category learning task after completing the reading span task within the same PsychoPy experiment.

Category Learning Task. The task was adapted from an earlier study by Le Pelley and colleagues (2019)**.** The category stimuli used in the present study were lines varying in length and angle. This category learning task was built into the same online experiment link as RSpan task on Pavlovia, the participants were presented with this task upon finishing the RSpan task. Each stimulus was a single blue line presented within a white square with gray borders. **Table 3.1** shows the parameters that were used to generate the stimuli for the CR and II categories, and **Figure 3.1** shows the resulting category structures. On each trial, the participants saw a line, along with the question “Does this line belong to Category A or Category B?”, to which they made a decision by pressing A or B on the keyboard. There was no timing constraint for responding. Feedback was provided immediately after the keyboard response. The participant was either shown the word “Correct” in green or “Wrong” in red (presented centrally for 600 ms), followed by a blank interval of 200 ms before the next trial began. Each participant completed 12 sets of 30 trials each (360 trials total), they had the option to take a self-paced break after each set of 30 trials. The CR task and II task had identical experimental setup. The reason that the categories within the II tasks are further away from the decision bound and formed tighter clusters than categories within the CR task is because these specific parameters encouraged above-chance performance. Our piloting data suggests that when similar stimuli spreadedness were used for the II task , it was more difficult to learn than the CR task.

Table 3.1: Parameters for stimulus generation in the conjunction and information integration conditions

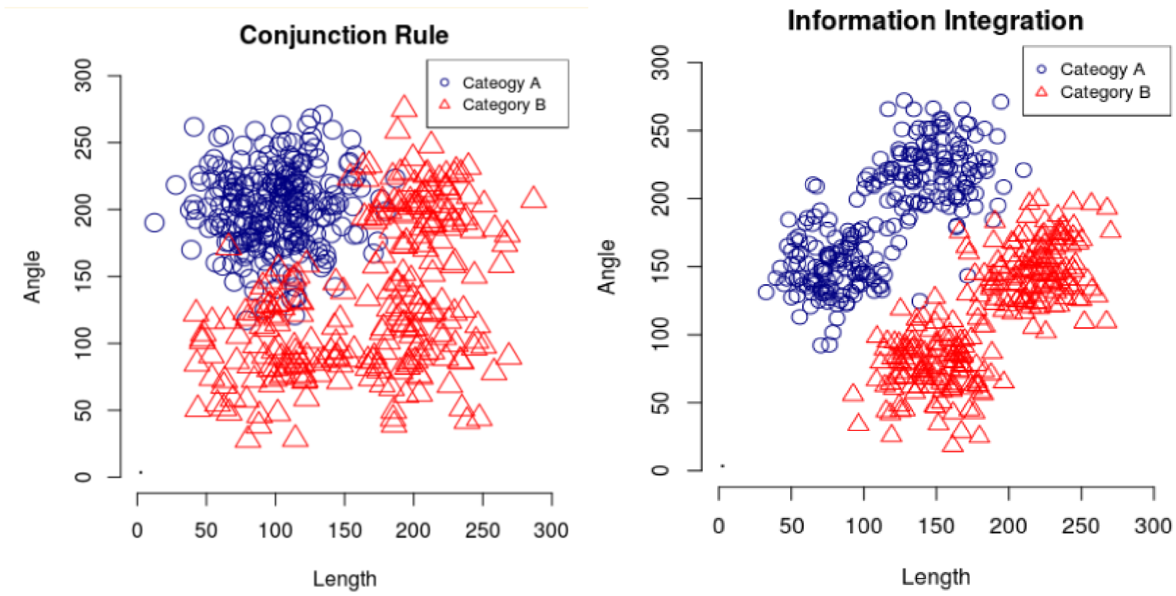
	Parameter	
Category	$\mu length$	$\mu angle$
Conjunction		
A	100	200
B	100	100
B	200	100
B	200	200
Information Integration		
A	80	150
A	150	220
B	150	80
B	220	150

Note: $\mu length$ and $\mu angle$ are the means of the normal distributions (CR: σ_{length}= 10 and $\sigma_{orientation}$= 900; II: σ_{length}= 30 and $\sigma_{orientation}$= 500) that were sampled to generate the length and angle (respectively) of the stimuli in the categorization task. For length, the given value was divided by 500 when presented on Pavlovia to give the length of the line stimulus in pixels. For angle, the given value was multiplied by $\pi/500$to give the angle of the line from horizontal in radians. The order of stimuli presentation was pseudorandomized, all participants of a given category structure received the exact same set of line stimuli in the same order. Half of the stimuli had Category A as the correct answer, and half had Category B as the correct answer.

Procedure

Participants signed up through either Western’s participant pool or Amazon MTurk. They clicked the provided link to access the ATQ which was hosted on Western’s Qualtrics server. At the end of the questionnaire, participants were given another link that re-directed them to Pavlovia--where the RSpan and category learning tasks were hosted. The entire process took on average 35 minutes, participants were compensated either 0.5 course credit or $2 for their time.

Figure 3.1: *The conjunction and information integration category structures used in Experiment 1*



Note. Values on each dimension refer to the length and angle of the line stimuli in the categorization task. Values are in arbitrary units.

Participants

CR Task. A total of 284 participants were recruited. All of them completed the ATQ on Qualtrics, but only 196 followed the instruction to complete the entire experiment (reading span and categorization task). Since the data for the two parts of the experiment were stored separately (Qualtrics and Pavlovia), each participant's data was linked by an unique ID which they were asked to enter in both parts of the experiment. However, among the 88 participants whose data was unusable, most have failed to enter an ID or entered a different ID on each part, which made it impossible to link the two parts for analyses. A smaller proportion of incomplete data was resulted from participants ending the experiment prematurely out of their own free will or browser issue when clicking the link to the second part.

The remaining 196 participants (Age: M = 21.56, SD = 9.72; 152 females/44 males; 17 from MTurk and 179 from Western University) completed all parts of the study along with the CR categorization task. See **Figure 3.2** for more participants' demographic information. Eight participants indicated they had a mental or physical impairment.

II Task. A total of 245 participants were recruited. However, 47 participants either did not enter the same unique ID on both parts of the experiment, terminated the experiment prematurely, or experienced browser issues upon clicking the link. The remaining 198 participants (Age: M = 18.90, SD = 1.26; 134 females/64 males; 7 from MTurk and 191 from Western University) completed all parts of the study along with the CR categorization task. See **Figure 3.3** for participants' ethnicity information. Nine participants indicated they had a mental or physical impairment.

Figure 3.2: *Pie Chart of Participants' Ethnicity (with number of participants per Ethnicity)*

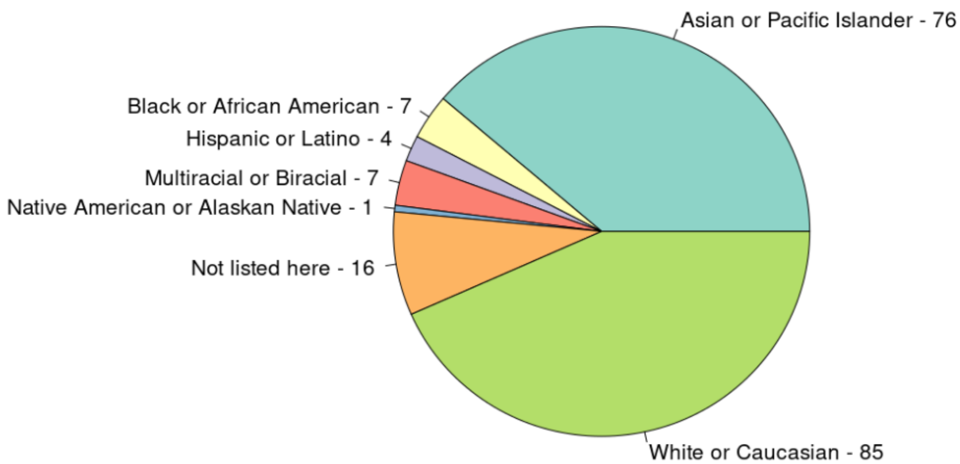
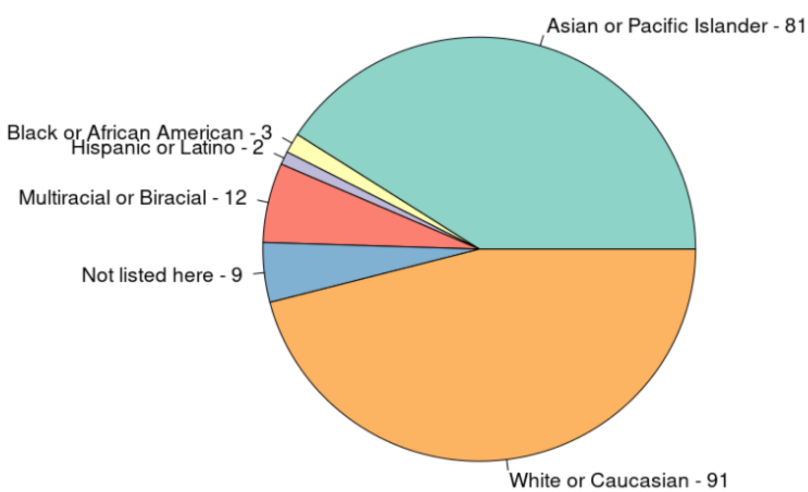


Figure 3.3: *Pie Chart of Participants' Ethnicity (with number of participants per Ethnicity)*



3.2.2. Analysis Plan

Performance Analysis

The CR and II categorization task each had 12 blocks of 30 trials. In the analysis, two subsequent blocks were combined into one larger block of 60 trials to be comparable to other studies that used similar tasks. All mentions of 'block' from now will be referring to these 60-trial blocks.

A multiple regression model was conducted for each type of categorization task to explore the relationships between temperament, working memory, and category learning. The dependent variable was the overall performance across all blocks. The independent variables were temperament traits (effortful control, negative affect and extraversion/surgency), interaction between each affective temperament trait and temperamental effortful control. Working memory measured by Rspan was also a predictor. The inclusion of the working memory in the models was intended to scrutinize the robustness of the temperament effects by having a previously-shown significant predictor of category learning to partial out variances in the dependent variable.

Decision Bound Computational Modeling

I also modeled participants' early category learning strategy by fitting five different models to the first block of each participant's categorization responses using the 'grt' package (Matsuki, 2014) in the R environment. This was intended to see whether participants' tendency to use rule or similarity-based strategies differ as a function of temperament traits and working memory.

The models differed in terms of the hypothesized boundaries that best divide the two categories in the category space shown in Fig. 1. The models used in this analysis were as follows:

The *unidimensional models* assume that the participants divide the two categories along one of the stimulus dimensions, either orientation or length. The unidimensional models I used had two parameters: the intercept value on the stimulus dimension of interest, and noise.

The *conjunction model* assumes that the participants incorporate both stimulus dimensional information to form an explicit rule, that they then use to divide the two categories. Specifically, participants evaluate each dimension separately first, then combine these evaluations to form a categorization decision. For instance, a conjunction rule can be "Assign to Category A if the line is short and the top is tilted to the left, otherwise assigned to Category B." The conjunction model I used had three parameters: the intercept value on each of the stimulus dimensions, and noise. This is the optimal strategy for learning the CR categorization task, I refer to this model as the CR strategy in the rest of the paper.

The *diagonal model* assumes that the best category-divider is a diagonal line. The stimulus dimensions need to be integrated prior to making a categorization judgment. The diagonal model has three parameters: the intercept and slope of the decision bound, and noise. This is the optimal strategy for learning the II categorization task, I refer to this model as the II strategy in the rest of the paper.

The *random guessing* models assume that there is no pattern behind participants' responses, this model has no parameters.

Maximum-likelihood parameter estimation was used by the grt package to determine the intercept (and slope) for each model that can best divide each participant's A and B responses. Next, I used the Bayesian information criterion (BIC: Schwarz, 1978) to select the best-fitting model for the two blocks of each participant.

A multinomial logistic regression analysis was conducted for each type of categorization task to explore the relationships between temperament, working memory, and the tendency to use rule-based or similarity-based strategy. The dependent variable was the strategy participants used in the first block of category learning. The independent variables were temperament traits (effortful control, negative affect and extraversion/surgency) and working memory measured by Rspan task. The interaction effect between each affective temperament and temperamental effortful control were not included because the first block responses should represent participants' default tendency to start learning a category. Effortful control should not modulate any biases until a certain strategy is perceived by the participants as superior and they need to consciously regulate their behavior and cognition to align with this strategy.

3.2.3. Results

3.2.3.1. CR Task

Analysis of Performance

Descriptive Results of Predictors. Of the 196 participants who completed all parts of the study, another 19 participants were flagged for corrupt or random responses (i.e., having lower than 60% on every single learning block, N = 6; had < 80% accuracy on meaningfulness judgment part of Rspan, N = 11; answered more than 100 words in the RSpan task, N = 2). Therefore, a total of 177 participants were used in the analysis. Temperament was measured through participants' self-report on the ATQ. The three temperament traits of interest were: negative affect, extraversion/surgency and effortful control. The negative affect subscale of ATQ consisted of 25 items (α = .79), the effortful control subscale consisted of 19 items (α = .85), and the extraversion/surgency subscale consisted of 17 items (α = .77). These were comparable to the Cronbach's Alpha values reported by Evans and Rotherbart (2007) which showed good internal consistency and high reliability. The final numerical score of each factor for each participant was calculated by adding up the ratings on all items associated with this factor, then dividing the total number of items. Negative affect scores ranged from 2.52 to 5.88 (*Median* = 4.40, *M* = 4.44, *SD* = 0.69); extraversion/surgency scores ranged from 2.35 to 6.71 (*Median* = 5.12, *M* = 4.99, *SD* = 0.87); effortful control scores ranged from 2.00 to 5.74 (*Median* = 4.00, *M* = 4.00, *SD* = 0.80) and reading span scores ranged from 24 and 60 (*Median* = 48, *M* = 46.23, *sd* = 7.62). **Table 3.2** shows the correlation matrix of the predictors in the main multiple regression model. There was a significant negative correlation between negative affect and effortful control, $r(177) = -0.502$, $p < .001$; and between negative affect and extraversion/surgency, $r(177) = -0.254$, $p < .001$.

Table 3.2: Correlation matrix of the criteria and predictors of CR category learning in Experiment 1.

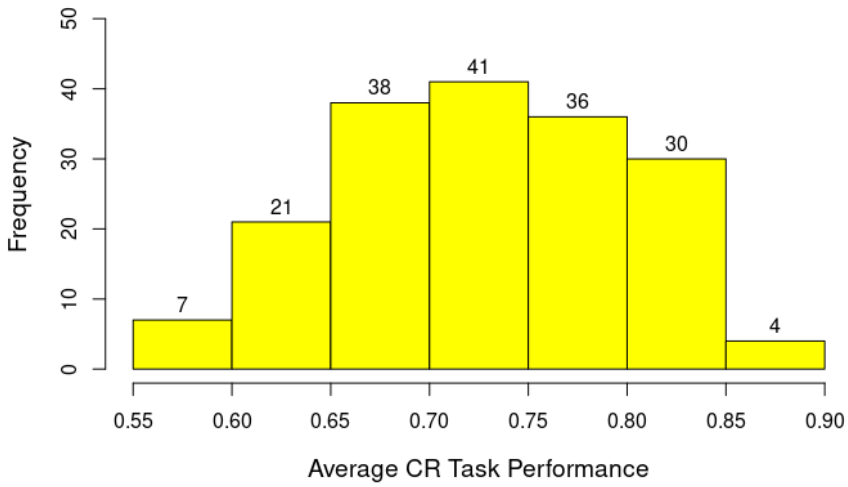
	Negative affect	Effortful control	Extraversion
Negative affect			
Effortful control	-0.502***		
Extraversion	-0.254***	-0.053	
Working Memory	-0.017	-0.070	0.053

*** $p < 0.001$
$N = 177$

Descriptive Results of the Dependent Variable. **Figure 3.4** shows the distribution of overall average CR category learning performance ($M = 0.73$, $SD = 0.072$). This histogram depicts an approximately normal distribution, with most participants' performance falling somewhere in the middle. **Figure 3.5** shows the distribution of each block performance with a line connecting the mean of each block. An ANOVA test was conducted to detect whether learning had occurred across the blocks. There was a significant learning effect, $F(5, 1056) = 14.35$, $p < .001$. Post hoc analysis of multiple comparisons among the blocks was done through Tukey HSD test, see **Figure 3.6** for more details. Interestingly, despite higher performance on block 3 and 5, the last block (block 6) performance did not differ significantly from the first block performance. This indicated an initial learning and a later fatigue effect.

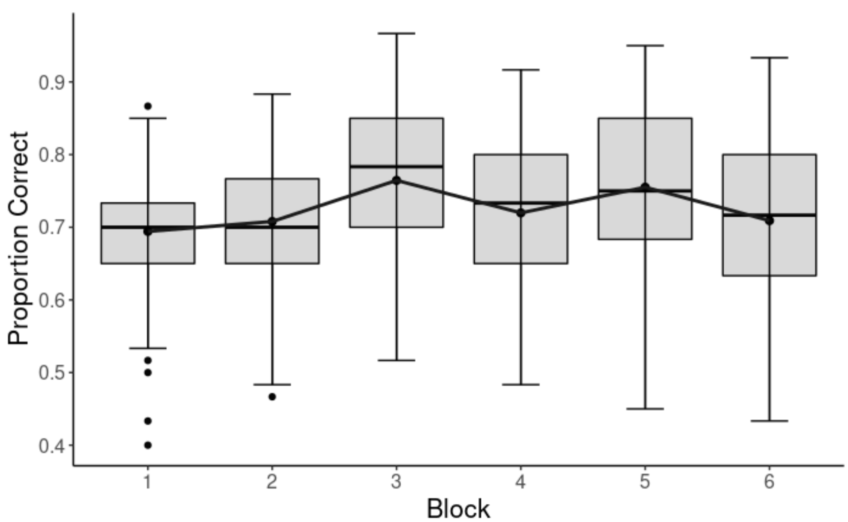
Multiple Regression Results. Before conducting the multiple regression model, I examined the correlational relationship between each individual predictor and the overall average CR performance. This is visualized in **Figure 3.7** as scatterplots.

Figure 3.4: *Distribution of the overall average CR performance in Experiment 1.*



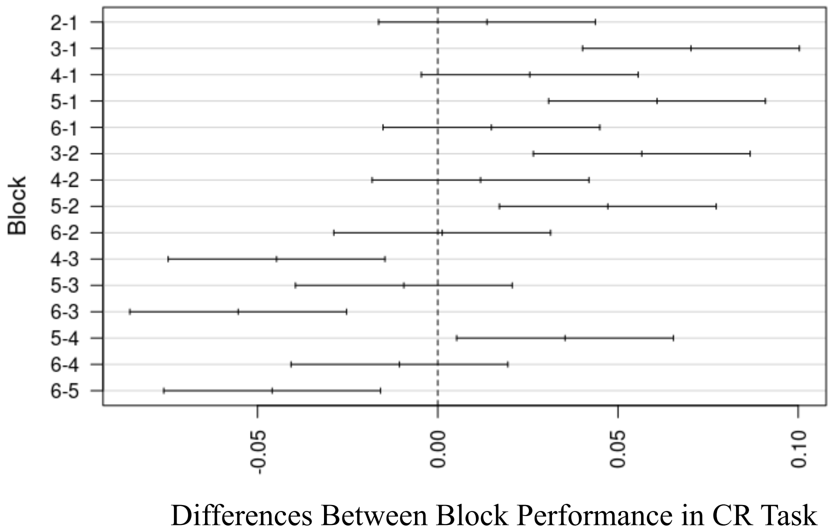
Note. The numeric above each bar shows the number of participants who fell in each range. $N = 177$

Figure 3.5: *Distribution of each CR block performance with a line connection block mean in Experiment 1*



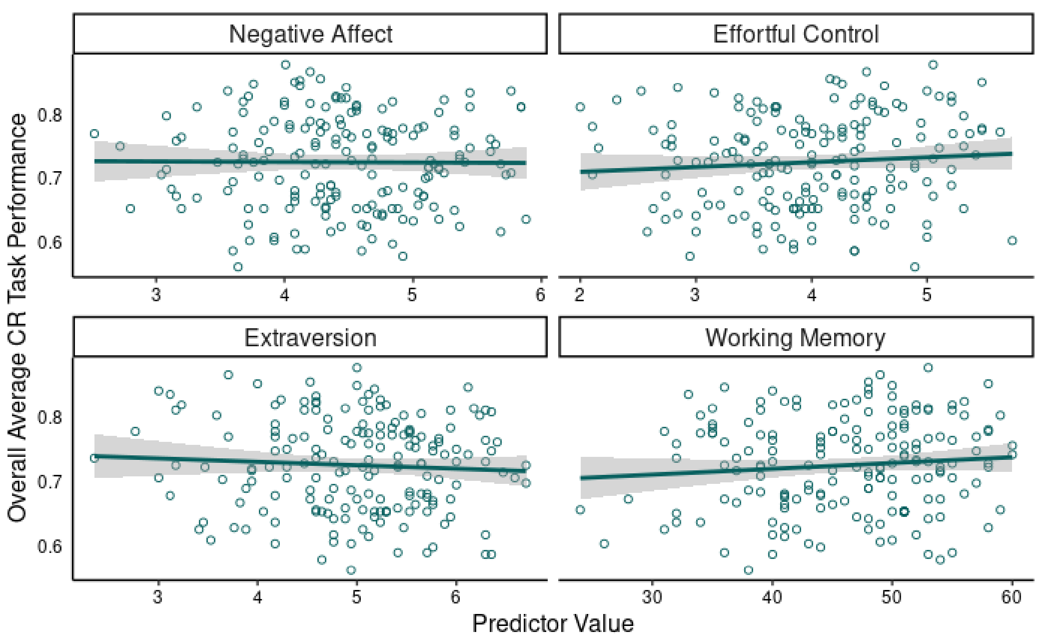
Note. For each block of CR performance, the box plot shows the interquartile range and median (box and horizontal line), and the mean and standard deviation (solid dot and vertical whiskers). The means across blocks are connected by a single line. $N = 177$.

Figure 3.6: *Tukey's HSD multiple comparisons between CR block performance with 95% confidence interval in Experiment 1*



Note. This plot depicts the multiple comparisons between any 2 blocks' performance for the CR task in Experiment 1. The x-axis represents the mean differences that were found between the pairs. The extended lines show the 95% confidence intervals. Confidence interval crosses 0 means the difference between blocks' performance is not significant at p = .05.

Figure 3.7: *Scatter plot depicting the correlational relationship between each predictor and overall average CR performance in Experiment 1.*



Note. Scatter plot for the temperament traits and working memory and their correlational relationship with overall average CR performance. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), with a line of best fit (line) and 95% confidence interval (gray zone) for the respective measure.

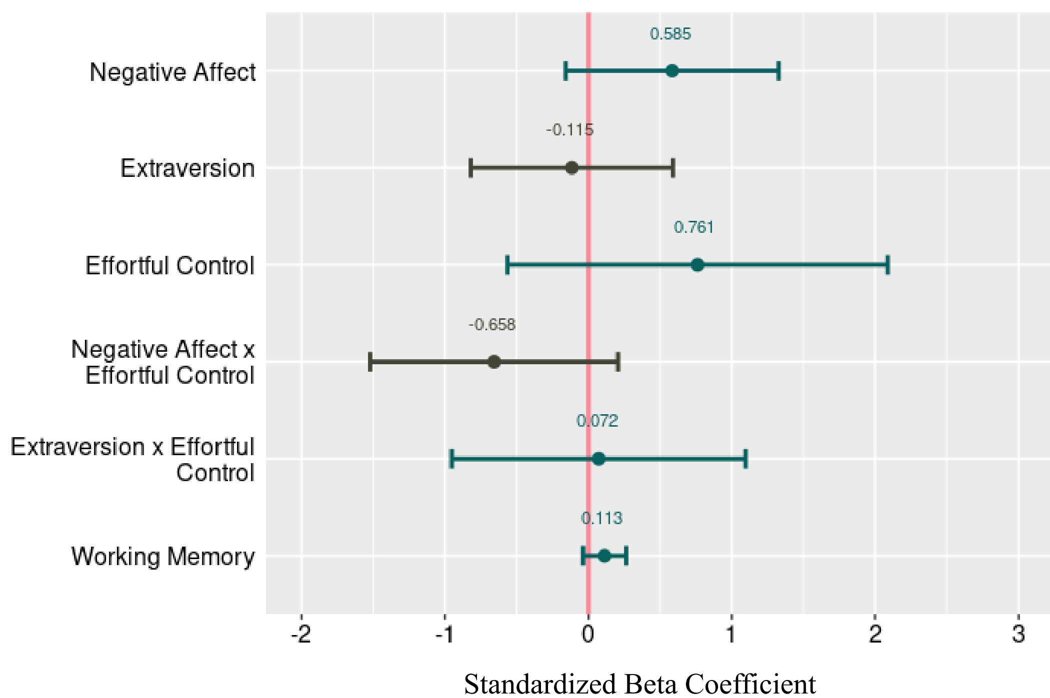
The full model regression predicting overall average CR performance was not significant, $F(6, 170) = 1.05$, $p = .39$. None of the predictors were significantly predictive. See **Table 3.3** for more details. These results can also be visualized in **Figure 3.8**.

Table 3.3: Full multiple regression model results predicting overall CR performance in Experiment 1

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(170)	*p*
Negative Affect	0.061	0.039	0.585	0.377	1.553	0.122
Extraversion	-0.010	0.030	-0.115	0.357	-0.321	0.749
Effortful Control	0.069	0.061	0.761	0.671	1.134	0.258
Negative Affect x Effortful Control	-0.014	0.010	-0.658	0.438	-1.504	0.135
Extraversion x Effortful Control	0.001	0.007	0.072	0.520	0.139	0.890
Working Memory	0.001	0.001	0.113	0.076	1.490	0.138

Note. Overall model was not significant, $F(6, 170)= 1.05$, $p = .39$, $R^2 = 0.036$, $R^2_{adj} = 0.002$. $N = 177$

Figure 3.8: *Standardized beta coefficient for full multiple regression model predicting overall average CR performance in Experiment 1.*



Note. Forest plot for the full multiple regression model. It depicts the model predicting overall average CR performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each predictor. Vertical line represents the neutral point or no relationship between the predictor and the criterion. $N = 177$.

The Backwards elimination process was done through the "step" function from the "stats" package in R (R Core Team, 2020). This procedure removed extraversion and the interaction between extraversion and effortful control as predictors from the model. Overall model was not significant, $F(4, 172) = 1.42$, $p = .23$. See **Table 3.4** for model statistics for the reduced model, and these results can also be visualized in **Figure 3.9**. Effortful control was approaching significance in the reduced model, [$\beta = 0.074$, $SE = 0.043$, $t(172) = 1.72$, $p = .087$], but neither this predictor nor the overall model was statistically significant. These results collectively suggest that neither temperament traits nor working memory were predictive of people's overall CR performance in the decision bound task.

Table 3.4: Reduced multiple regression model results predicting overall CR performance in Experiment 1

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(172)	p
Negative Affect	0.062	0.039	0.593	0.371	1.598	0.112
Effortful Control	0.074	0.043	0.811	0.472	1.720	0.087
Negative Affect x Effortful Control	-0.014	0.009	-0.639	0.427	-1.497	0.136
Working Memory	0.001	0.001	0.111	0.075	1.476	0.142

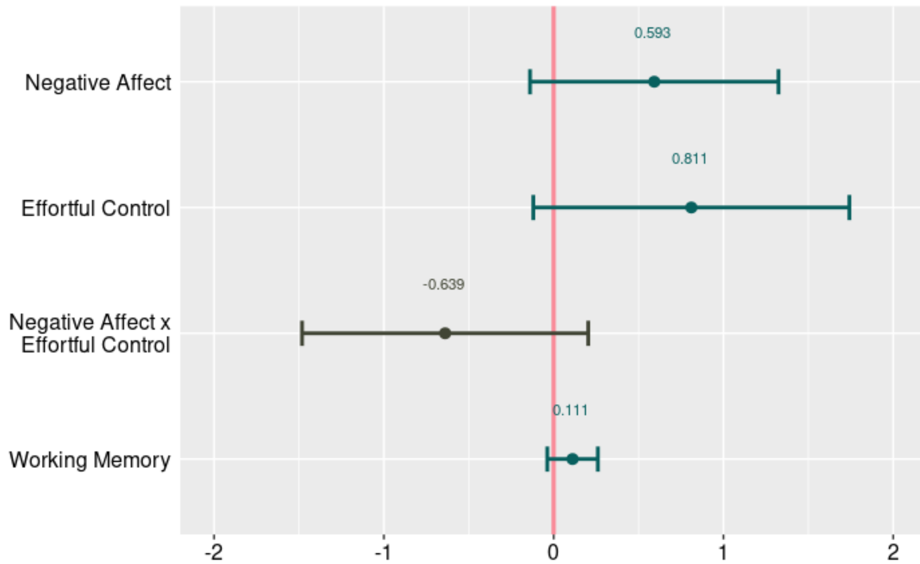
Note. Overall model was not significant, $F(4, 172) = 1.42$, $p = .23$, $R^2 = 0.032$, $R^2_{adj} = 0.009$. $N = 177$

Strategy Analysis

Descriptive Results of the Dependent Variable. Before conducting the multinomial logistic regression model with the first block strategy as the dependent variable, I examined the correlational relationship between each individual predictor and the first block CR performance with each strategy being depicted in a different color. This is visualized in **Figure 3.10** as scatterplots.

As can be seen in Figure 3.10, most participants were best fitted by the single dimensional rule strategy ($N = 124$) and a very small number of participants were best fit by the optimal CR strategy ($N = 11$). These two types of strategies were combined to form one rule-based strategy group because the CR sample was too small as its own group for analysis. Participants who were best fitted by a II model ($N = 28$) and a random model ($N = 14$) were also included in the strategy analysis. I intended to explore through this analysis whether the tendency to use rule or II strategy differ as a function of temperament traits or working memory. The random model was used as the baseline, and a predictor's coefficient represents whether one unit change in this predictor is associated with an increase or a decrease in the log odds of using another strategy compared to random strategy.

Figure 3.9: *Standardized beta coefficient for the reduced multiple regression model predicting overall average CR performance in Experiment 1*



Standardized Beta Coefficient

Note. Forest plot for the full multiple regression model. It depicts the reduced model predicting overall average CR performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each predictor. Vertical line represents the neutral point or no relationship between the predictor and the criterion. $N = 177$.

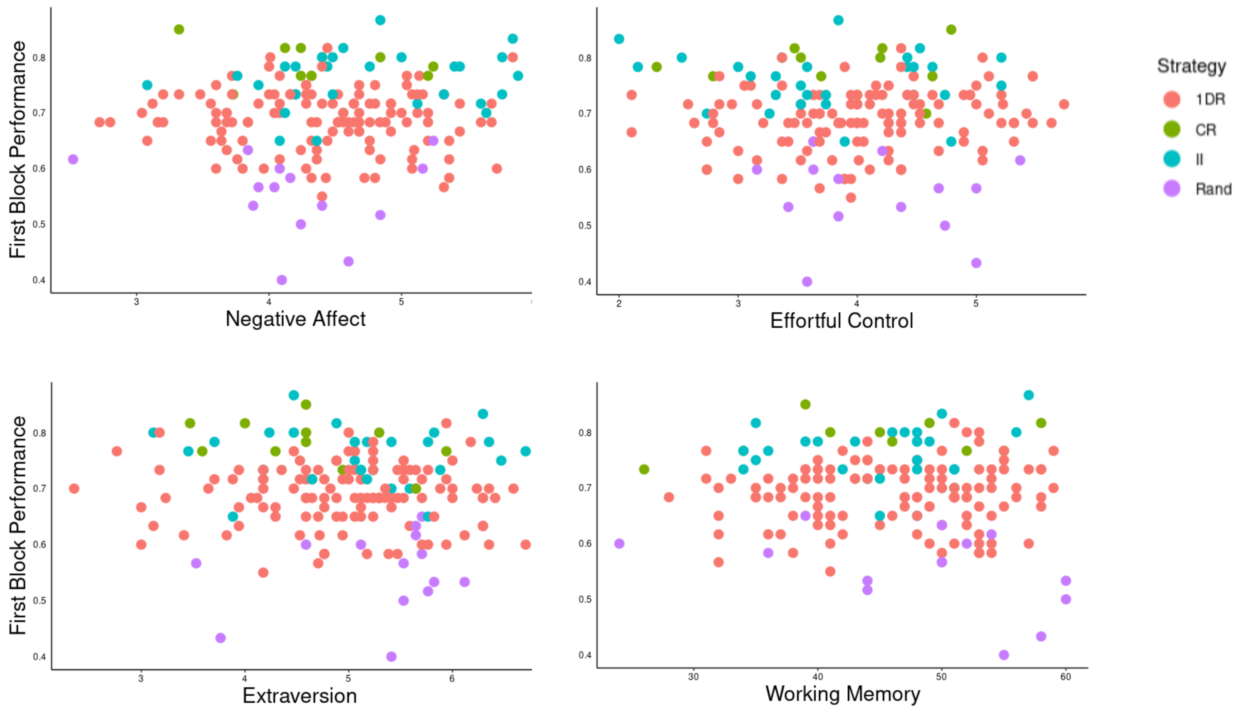
Compared to participants whose first block was best fitted by a random model, changes in negative affect [$\beta = 0.093$, $SE = 0.522$, $p = .86$], effortful control [$\beta = -0.259$, $SE = 0.443$, $p = .56$] and extraversion [$\beta = -0.456$, $SE = 0.379$, $p = .23$] did not make people more likely to use a single dimensional rule-based strategy; and changes in negative affect [$\beta = 0965$, $SE = 0.630$, $p = .13$], effortful control [$\beta = -0.309$, $SE = 0.521$, $p = .55$] and extraversion [$\beta = -0.061$, $SE = 0.445$, $p = .89$] also did not make people more likely to use the II strategy. Working memory was not associated with increases or decreases in using a single dimensional rule [$\beta = -0.040$, $SE = 0.041$, $p = .33$], or an II strategy [$\beta = -0.055$, $SE = 0.047$, $p = .24$]. These results seem to suggest that people tend to use a simple rule-based approach as their default approach in category learning, and this tendency is irrespective of their temperament traits or working memory.

3.2.3.2. II Task

Analysis of Performance

Descriptive Results of Predictors. Of the 198 participants who completed all parts of the study, a total of 38 participants were flagged for corrupt or random responses (i.e., having lower than 60% on every single learning block or had <80% accuracy on meaningfulness judgment part of Rspan). Therefore, a total of 160 participants were used in the analysis.

Figure 3.10: *Scatter plot depicting the correlational relationship between each predictor and first block CR performance in Experiment 1 with each strategy being depicted by a different color.*



Note. Scatter plot for the temperament traits and working memory and their correlational relationship with first block CR performance. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), dot colors represent the type of strategy each participant's responses was best fitted by. $N = 177$

The negative affect subscale of ATQ consisted of 25 items (α = .77), the effortful control subscale consisted of 19 items (α = .77), and the extraversion/surgency subscale consisted of 17 items (α = .73). These were comparable to the Crobach's Alpha values reported by Evans and Rotherbart (2007) which showed good internal consistency and high reliability. The negative affect scores ranged from 2.88 to 6.52 (*Median* = 4.48, *M* = 4.50, *SD* = 0.62; extraversion/surgency scores ranged from 2.35 to 6.59 (*Median* = 5.05, *M* = 5.03, *SD* = 0.75); effortful control scores ranged from 1.68 to 5.37 (*Median* = 3.79, *M* = 3.79, *SD* = 0.71) and reading span scores ranged from 25 and 60 (*Median* = 47.50, *M* = 46.54, *SD* = 8.45). **Table 3.5** shows the correlation matrix of the predictors in the main multiple regression model. There was a significant negative correlation between negative affect and effortful control, $r(158) = -0.397$, $p < .001$; and between negative affect and extraversion/surgency, $r(158) = -0.399$, $p < .001$. There was a significant positive correlation between extraversion/surgency and effortful control, $r(158) = 0.229$, $p < .01$. This correlation was not seen in the participant sample who completed the CR task.

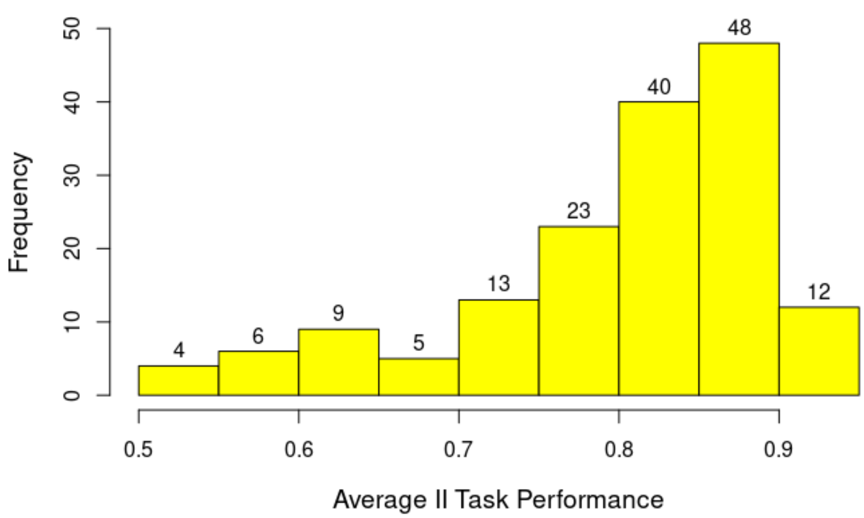
Table 3.5: Correlation matrix of the criteria and predictors of II category learning in Experiment 1

	Negative affect	Effortful control	Extraversion
Negative affect			
Effortful control	-0.397***		
Extraversion	-0.399***	0.229**	
Working Memory	0.018	-0.021	0.015

*** Correlation is significant at p = 0.001 level
** Correlation is significant at p = 0.01 level
N = 160

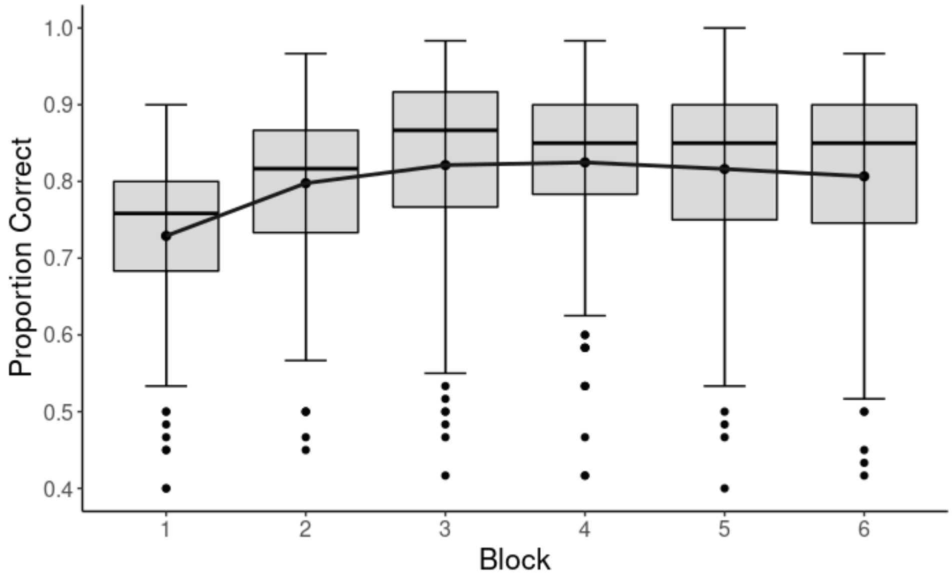
Descriptive Results of the Dependent Variable. **Figure 3.11** shows the distribution of overall average II category learning performance (M = 0.78, SD = 0.12). This histogram depicts a left skewed distribution, suggesting that most participants achieved a high overall performance. **Figure 3.12** shows the distribution of each block performance with a line connecting the mean of each block. An ANOVA test was conducted to detect whether learning has occurred across the blocks. There was a significant effect of learning, $F(5, 1056) = 14.35$, $p < .001$. Post hoc analysis of multiple comparisons among the blocks was done through Tukey HSD test, see **Figure 3.13** for more details. Interestingly, most participants seemed to have learned this task by block 2, and there was no significant performance improvement after that. This indicated an initial learning and a later fatigue effect.

Figure 3.11: *Distribution of overall II performance in Experiment 1*



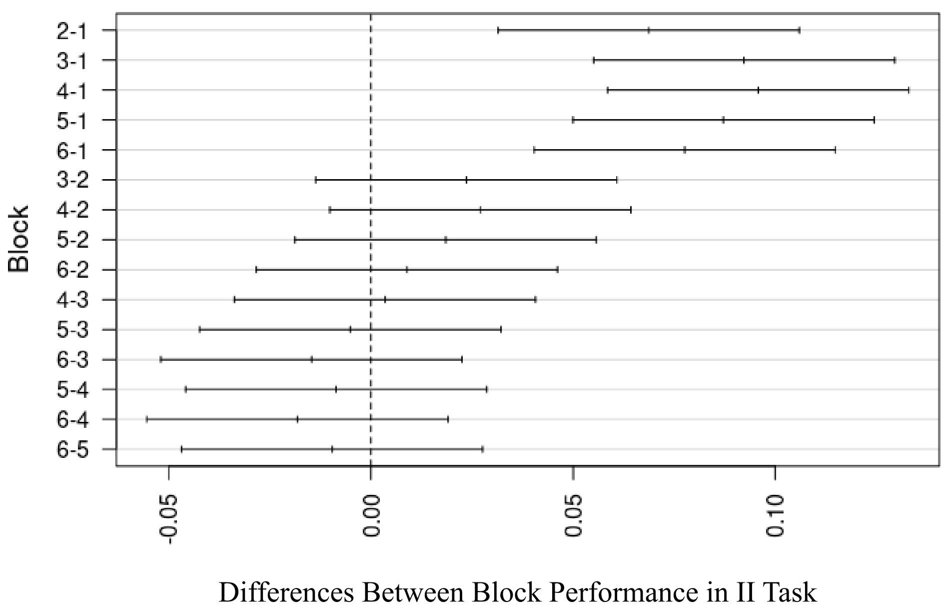
Note. The numeric above each bar shows the number of participants who fell in each range.

Figure 3.12: *Distribution of each II block performance with line connection block mean in Experiment 1*



Note. For each block of II performance, the box plot shows the interquartile range and median (box and horizontal line), and the mean and standard deviation (solid dot and vertical whiskers). The means across blocks are connected by a single line. $N = 160$.

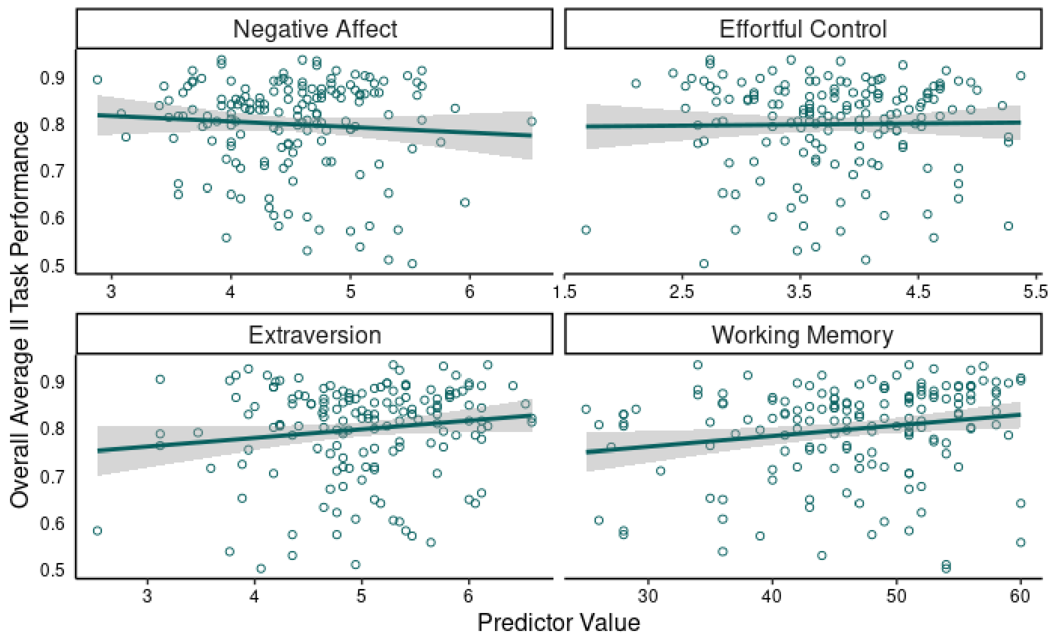
Figure 3.13. *Tukey's HSD multiple comparisons between II block performance with 95% confidence interval*



Note. This plot depicts the multiple comparisons between any 2 blocks' performance for the II task in Experiment 1. The x-axis represents the mean differences that were found between the pairs. The extended lines show the 95% confidence intervals. Confidence interval crosses 0 means the difference between blocks' performance is not significant at p = .05.

Multiple Regression Results. Before conducting the multiple regression model, I examined the correlational relationship between each individual predictor and the overall average II performance. This is visualized in **Figure 3.14** as scatter plots.

Figure 3.14: *Scatter plot depicting the correlational relationship between each predictor and overall average II performance in Experiment 1.*



Note. Scatter plot for the temperament traits and working memory and their correlational relationship with overall average II performance. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), with a line of best fit (line) and 95% confidence interval (gray zone) for the respective measure.

The full model regression predicting overall average II performance was not significant, $F(6, 153) = 1.73$, $p = .12$. Among the predictors, only working memory was significantly predictive of average II performance, [$\beta = 0.002$, $SE = 0.001$, $t(153) = 2.39$, $p = .018$], see **Table 3.6** for details. These results can also be visualized in **Figure 3.15**.

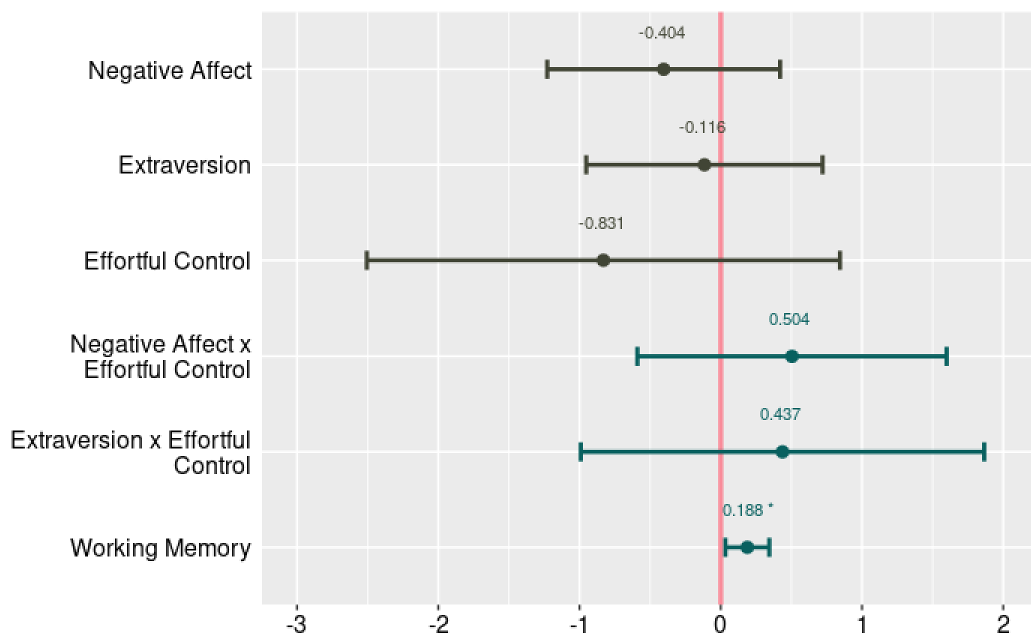
After the backwards elimination, only extraversion/surgency and working memory were left in the model as predictors. The reduced model regression predicting overall average II performance was significant, $F(2, 157) = 4.70$, $p = .010$. See **Table 3.7** for model statistics for the reduced model and these results can also be visualized in **Figure 3.16**. Working memory was statistically significant, [$\beta = 0.002$, $SE = 0.001$, $t(157) = 2.47$, $p = .015$] and extraversion/surgency was approaching significance, [$\beta = 0.018$, $SE = 0.007$, $t(157) = 1.78$, $p = .078$]. These results suggest that working memory significantly contributed to people's overall II category learning performance in the positive direction, and the facilitatory effect of extraversion/surgency was marginally significant.

Table 3.6: Full multiple regression model results predicting overall II performance in Experiment 1

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(153)	*p*
Negative Affect	-0.064	0.066	-0.404	0.417	-0.969	0.334
Extraversion	-0.015	0.055	-0.116	0.424	-0.274	0.785
Effortful Control	-0.116	0.118	-0.831	0.848	-0.980	0.329
Negative Affect x Effortful Control	0.016	0.017	0.504	0.554	0.910	0.364
Extraversion x Effortful Control	0.009	0.014	0.437	0.723	0.604	0.546
Working Memory	**0.002**	**0.001**	**0.188**	**0.079**	**2.391**	**0.018**

Note. Overall model was not significant, $F(6, 153) = 1.73$, $p = .12$, $R^2 = 0.064$, $R^2_{adj} = 0.027$. $N = 160$

Figure 3.15: *Standardized beta coefficient for full multiple regression model predicting overall average II performance in Experiment 1*



Standardized Beta Coefficient

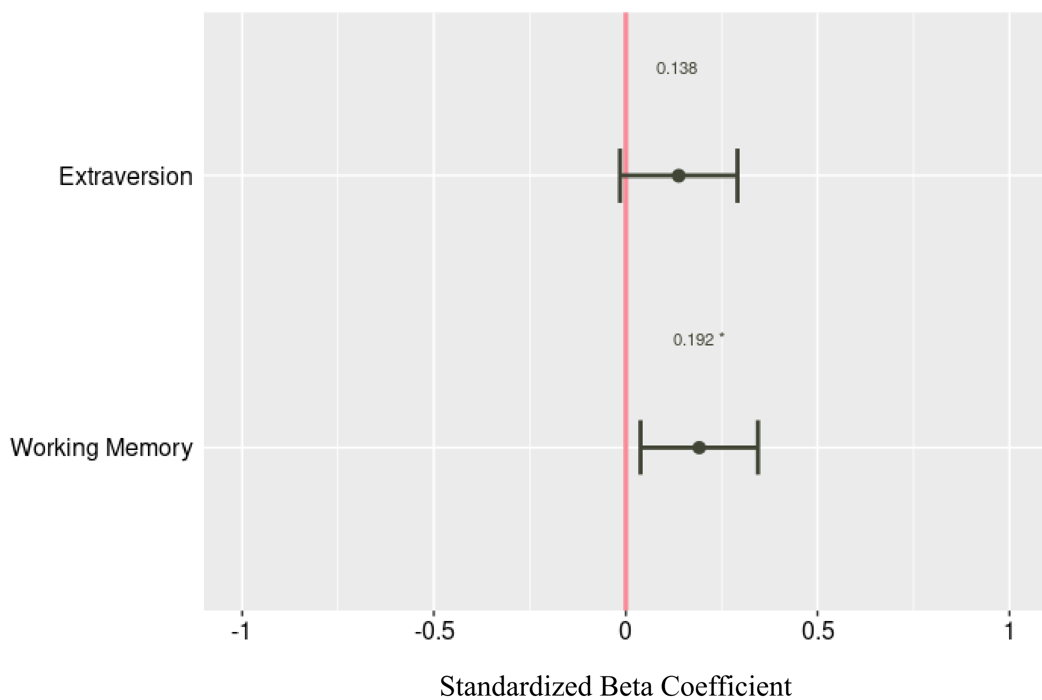
Note. Forest plot for the full multiple regression model. It depicts the model predicting overall average II performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion.

Table 3.7: Reduced multiple regression model results predicting overall II performance in Experiment 1

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(170)	p
Extraversion	0.018	0.010	0.138	0.078	1.777	0.078
Working Memory	**0.002**	**0.001**	**0.192**	**0.078**	**2.472**	**0.015**

Note. Overall model was not significant, $F(2, 157) = 4.70$, $p = .010$, $R^2 = 0.057$, $R^2_{adj} = 0.045$. $N = 160$

Figure 3.16: *Standardized beta coefficient for the reduced multiple regression model predicting overall average II performance in Experiment 1.*



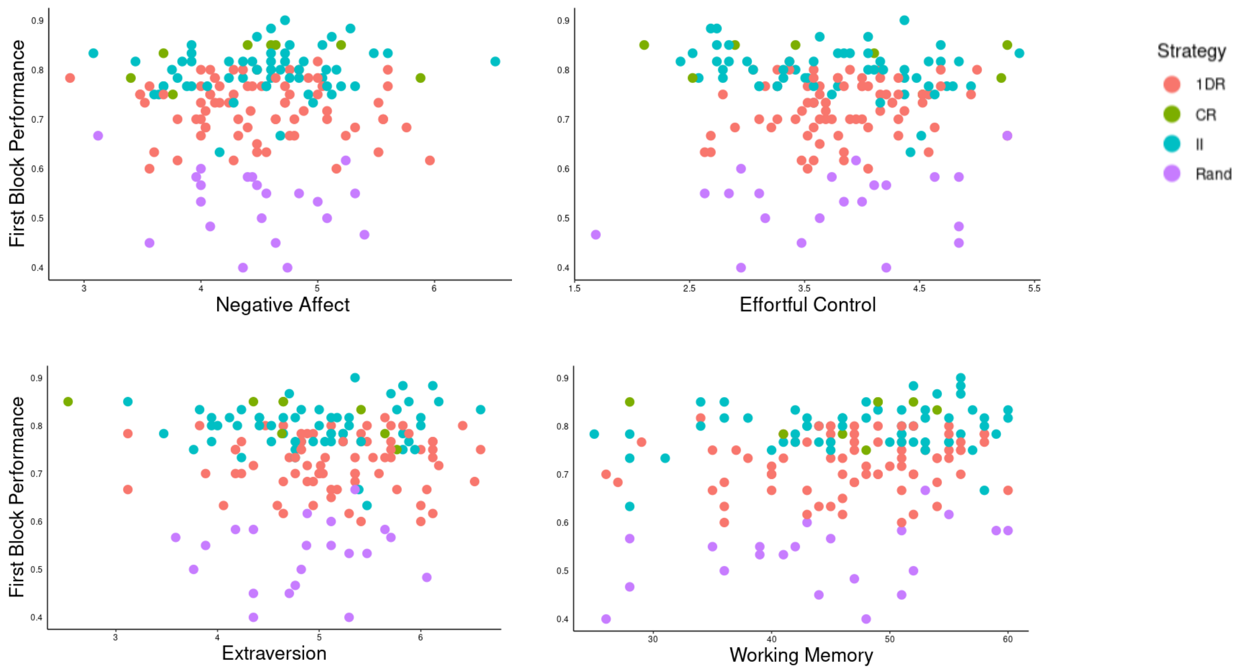
Note. Forest plot for the reduced multiple regression model. It depicts the model predicting overall average II performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion.

Strategy Analysis

Descriptive Results of the Dependent Variable. Before conducting the multinomial logistic regression model with the first block strategy as the dependent variable, I examined the correlational relationship between each individual predictor and the first block II performance with each strategy being depicted in a different color. This is visualized in **Figure 3.17** as scatterplots.

As can be seen in **Figure 3.17**, about half of participants were best fitted by the single dimensional rule strategy ($N = 74$) and a very few participants were best fitted by the optimal CR strategy (N = 8). These two types of strategies were combined to form one rule-based strategy group because the CR sample was too small as its own group for analysis. Participants who were best fitted by a II model (N = 57) and a random model (N = 21) were also included in the strategy analysis. I intended to explore through this analysis whether the tendency to use rule or II strategy differ as a function of temperament traits or working memory. The random model was used as the baseline, and a predictor's coefficient represents whether one unit change in this predictor is associated with an increase or a decrease in the log odds of using another strategy compared to random strategy.

Figure 3.17: *Scatter plot depicting the correlational relationship between each predictor and first block II performance in Experiment 1 with each strategy being depicted by a different color.*



Note. Scatter plot for the temperament traits and working memory and their correlational relationship with first block II performance. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), dot colors represent the type of strategy each participant's responses was best fitted by. N = 160

Compared to participants whose first block was best fitted by a random model, changes in negative affect [β = 0.427, SE = 0.489, p = .38], effortful control [β = 0.138, SE = 0.383, p = .72] and extraversion [β = 0.574, SE = 0.349, p = .10] did not make people more likely to use a single dimensional rule-based strategy; and changes in negative affect [β = 0.382, SE = 0.506, p = .45], effortful control [β = 0.084, SE = 0.396, p = .83] and extraversion [β = 0.285, SE = 0.357, p = .42] also did not make people more likely to use the II strategy. Working memory was not associated with increases or decreases in using a single dimensional rule [β = 0.036, SE = 0.028, p = .20], or an II strategy [β = 0.046, SE = 0.030, p = .12]. These results seem to suggest that people tend to use a simple rule-based approach as their default approach in category learning, and this tendency is irrespective of their temperament traits or working memory.

3.2.4. Interim Discussion

Learning occurred in both category learning tasks. In the CR task, participants' performance continued to improve until block 5, but a fatigue effect was observed in the last block. In the II task, significant learning happened only between block 1 and block 2, suggesting most people reached their peak performance fairly quickly. Results from multiple regression analyses showed that temperament traits were not predictive of either CR or II category learning performance. One surprising result emerged from these analyses – working memory significantly predicted people's overall performance on the II task, but not on the CR task. This result was surprising because previous studies have generally suggested that working memory should be facilitatory of CR learning (Maddox et al., 2004; Waldron & Gregory Ashby, 2001; Zeithamova & Maddox, 2006), where the inconsistencies are often regarding its association with II learning (Craig & Lewandowsky 2012; Lewandowsky et al. 2012).

Participants differed in their default strategy in both CR and II tasks. The majority of participants in both tasks were best fitted by a single dimensional rule model. Task structure differentiated the proportion of participants using each type of strategy. A total of 81% participants used a rule-based strategy in the CR task, while only 16% used an II strategy. On the other hand, a total of 36% participants used an II strategy, and about half of participants used a rule-based strategy. Despite the strategy use differences across participants and tasks, temperament traits and working memory generally were not found to be predictive of strategy tendency.

There were two potential limitations in Experiment 1. First, this specific version of II task may be perceived by most participants as too easy. This may be due to an arbitrarily selected larger category separability parameter value around the decision-bounds for the II task than the CR task. A larger parameter value was used for II task because none of the 30 pilot participants performed above chance when the parameter values matching the CR task were used. Another pilot sample of 20 participants tested the new II category separability parameter values and showed learning effect and performance variation, thus I decided to use these values. However, the full data performance distribution suggested that the majority of participants perceived the II task as easy, and this ceiling effect may potentially undermine the relationship between temperament traits and similarity-based category learning.

Second, Experiment 1 used a between-subject design where different people completed the CR and II category learning tasks. This was not necessarily a limitation since we did not intend to compare CR task performance with II task performance. However, if the same participants completed both tasks in the same setting, we would be able to control for a list of spurious variables (e.g., time of the day, hours of sleep the previous night) that may potentially influence category learning performance. A within-subject design may show more robust results about temperament effects across tasks.

In Experiment 2, I examined the same temperament effects on learning a different set of CR and II categories. Compared to the task used in Experiment 1 where the stimuli varied on two continuous dimensions and category decisions can be mapped by one or more lines through the category space, the tasks in Experiment 2 used stimuli with binary dimensions where category decisions are based on presence or absence of relevant features. The binary task avoided the issues with different perceived difficulty between tasks as seen in Experiment 1. Moreover, a within-subject design was implemented.

3.3. Experiment 2

3.3.1. Methods

Materials

Adult Temperament Questionnaire. (ATQ; Evans & Rothbart, 2007) The ATQ used in Experiment 2 was identical to Experiment 1. This questionnaire was hosted on Qualtrics (https://mysurveys.uwo.ca/). At the end of the ATQ, the participants were given a clickable link which will redirect them to Pavlovia (pavlovia.org) to complete the next two tasks.

Reading Span Task. (RSpan; Daneman & Carpenter, 1980) The reading span task used in Experiment 2 was identical to that of Experiment 1.

Category Learning Task. (adapted from Xie et al., 2015). I used color images of houses as category learning stimuli. Each stimulus was composed of four dimensions with each dimension having one of the two possible values. The four dimensions and possible features were roof shape (triangle vs. mountain shape), number of windows (2 vs. 3), color of the house (blue vs. pink), and type of tree (green vs. orange). There were 16 stimuli in total.

The optimal strategy in the rule-based task was again of a conjunctive structure. For the **CR task**, categories were arbitrarily defined by selecting two dimensions as relevant and the remaining two dimensions as irrelevant. The values of 1 and -1 were arbitrarily assigned to each relevant dimension (e.g., triangle shaped roof = 1, mountain shaped roof = -1). Category A stimuli were the ones that had value 1 on both of the relevant dimensions (4 unique stimuli), and category B stimuli were the ones that had value -1 on at least one relevant dimension (12 unique stimuli). There was a comparable number of A and B stimuli in the experiment. This means that the frequency of appearance for each unique A stimulus was approximately three times that of any unique B stimulus. However, the exact number of each stimulus within a category differed slightly to ensure that the pseudo-randomized stimuli presentation order did not have any 10 consecutive trials that can be best-fitted by another model than the designated one. Ten was set to be the criterion in this study just as in Xie et al., participants who got 10 correct trials in a row were deemed learners of the optimal strategy. There were 200 trials in total in the CR task, and all participants viewed the stimuli in the same pseudo-randomized order. I also counterbalanced the relevant dimensions, which yielded 6 possible combinations of two dimensions out of the total four dimensions. See **Figure 3.18** for a schematic of one possible CR task.

Figure 3.18: *An example of CR task condition used in Experiment 2*

Note. A schematic of one possible CR task condition in which the shape of roof (triangle vs. squiggly) and number of windows (2 vs. 3) dimensions are relevant. Category A stimuli are in the box with gray background (upper left) and the remaining stimuli belong to Category B.

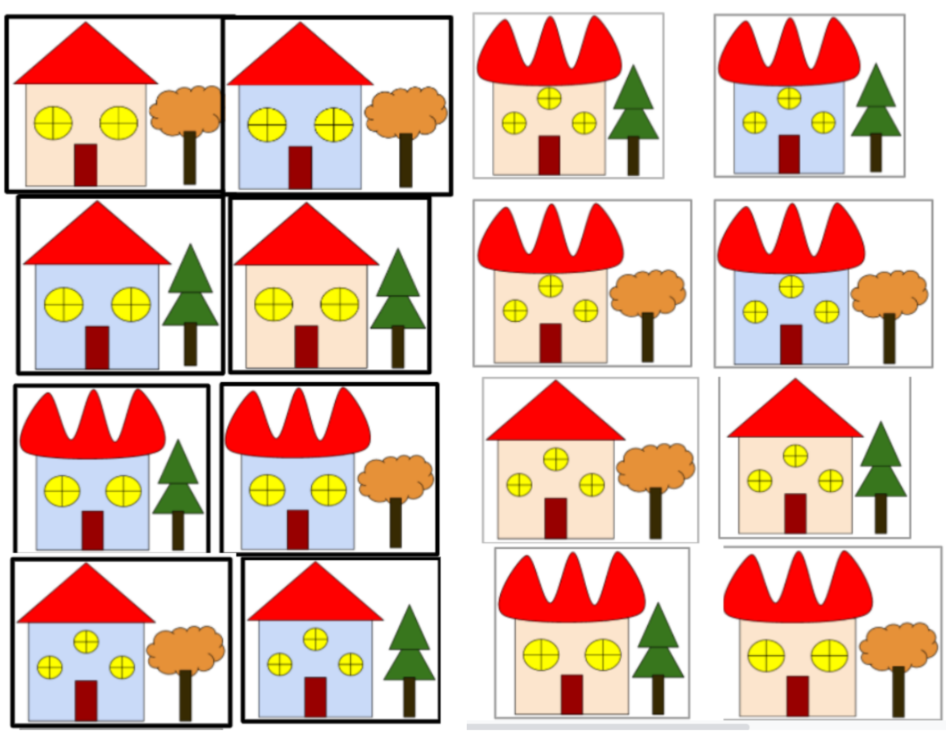
The similarity-based task used here again required a holistic information-integration (II) strategy to best learn. For the **II task**, I first rendered one dimension irrelevant. Then the values of 1 or -1 were arbitrarily assigned to each of the remaining relevant dimensions. The categories were formed following the equation below, where X, Y, and Z represents the value assigned to each dimension:

$$\textbf{If } X + Y + Z > 0 \textbf{, then "A", else "B"}$$

Another way to interpret this category is that it follows polymorphous classification or an n-out-of-m rule (Murdoch et al., 1951). For example, the stimuli used in this study vary in four dimensions of roof shape (triangle or squiggly), window number (two or three), wall color (pink or blue) and tree type (triangle or round). If tree type was deemed to be the irrelevant feature and one polymorphous category would be defined by the rule "Category A is at least two of triangle roof, blue wall and two windows." Even though the category structure can be described by a rule, polymorphous classification is a form of overall similarity classification characterized by a set of "family resemblances"(Wills et al., 2020).

This yielded 8 unique category A and 8 unique category B stimuli. There were 200 trials in total in the II task and all participants viewed the stimuli in the same pseudo-randomized order. Just like in the rule-based task, the number of category A and B stimuli was comparable while the number of within-category stimuli differed slightly. The relevant dimensions were again counterbalanced, which yielded 4 possible combinations of three dimensions out of the total four dimensions. See **Figure 3.19** for a schematic of one possible II task.

Figure 3.19: *An example of II task condition used in Experiment 2*



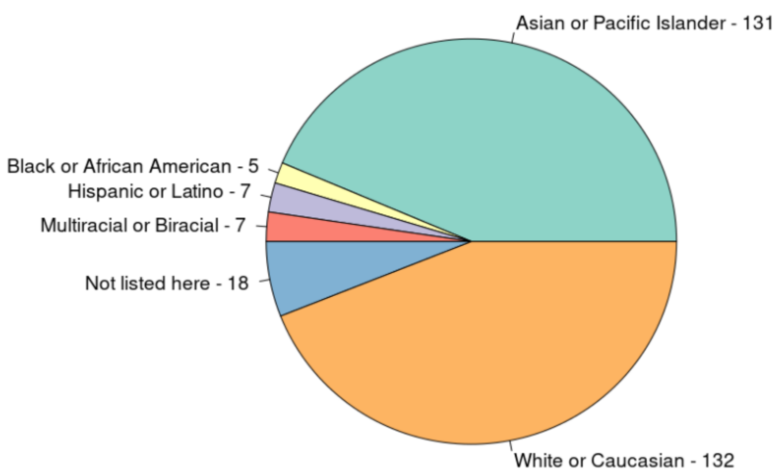
Note. A schematic of one possible II task condition in which the tree dimension is irrelevant. Category A stimuli have black borders and Category B stimuli have light gray borders.

On each trial, the participants saw a house stimulus, along with the question "Does this house belong to Category A or Category B?", to which they made a decision by pressing A or B on the keyboard. There was no timing constraint for responding. Feedback was provided immediately after the keyboard response. The participant was either shown the word “Correct” in green or “Wrong” in red (presented centrally for 600 ms), followed by a blank interval of 200 ms before the next trial began. Participants were informed that their goal was to get as many correct trials in a row as possible within the 200 trials. The CR and II category learning tasks had the same setup, but the stimuli and response association were different.

Participants

Three-hundred undergraduate students from Western Universiry aged 17-25 yr (M = 18.33, SD = 0.89; 233 female, 62 male, 5 gender non-conforming) completed the study. The reasons for the large sample of 300 were twofold, both to detect small effects in individual differences and to take into account the possibility of random-responders in online experiments. Temperament traits were measured through participants’ self-report on the ATQ. **Figure 3.20** shows the proportion of participants belonging in each ethnicity group (with counts).

Figure 3.20: *Pie Chart of Participants' Ethnicity (with number of participants per Ethnicity)*



Procedure

Participants signed up through Western’s SONA pool and clicked on the online study link to participate in the study. The link took participants to Qualtrics where the letter of information was provided. They clicked the corresponding box to indicate implied consent then completed the ATQ that followed. At the end of the ATQ participants were automatically redirected to Pavlovia to complete the first category learning task, Rspan task and the second category learning task. Participants were asked to enter their anonymized unique ID at the end of the ATQ and at the beginning of the Pavlovia tasks in order to link their responses across platforms together.

3.3.2. Analysis Plan

Two multiple regression analyses were conducted for each type of category learning task to examine whether temperament traits or working memory can predict people's overall category learning performance and optimal strategy learning rate, respectively.

Both regression models had identical independent variables: the three temperament traits (negative affect, extraversion/surgency, effortful control), the interaction between each affective temperament and effortful control. Working memory (measured by RSpan) was also a predictor in the models. CR category condition (i.e., conditions differed in the relevant dimensions that composed the rule) and category order (i.e., either CR task first or II task first) were added to the models to ensure internal validity by controlling the potential confounds created by condition and order effects. The dependent variables were overall categorization performance (the first series of regression analyses) and rate of optimal strategy learning (trials-to-criterion: the second series of regression analyses).

The analyses of overall performance included both learners (reached criterion during the task) and non-learners, whereas the analyses of TTC only included learners. Results from the two series of analyses complemented each other in capturing participants' learning behavior. Specifically, looking at overall performance on its own can be misleading because a certain group of participants may have reached good performance (~70%) without ever learning the optimal strategy. Similarly, only examining TTC may not distinguish participants who (although highly unlikely[6]) reached the criterion by chance and performed poorly afterwards. Moreover, there may be learners that reached criterion at a later stage of learning after going through many rounds of strategy switches and low performance, TTC analysis was able to capture these eventual-learners better than simply flagging them as low performers which would happen in analysis of overall performance. Results from these two analyses needed to be looked at together and consistent patterns can be then interpreted.

3.3.3. Results

General Data Cleaning

A total of 48 participants were excluded from analyses for the following reasons: 1) completed the ATQ (77 items) in less than 5 minutes ($N = 8$); 2) had less than 80% correct on the judgment part of the RSpan task, which can be seen as an attention check ($N = 32$). Lewandowsky and colleagues (2010) who developed the task used a cutoff of 85%, I used a more lenient but still reasonable criterion to avoid removing good participants; 3) answered more than 100 words in

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[6] The stimuli presentation order ensured that no 10 consecutive trials can be answered correctly using a strategy other than the optimal designated one.

the RSpan task (*N* = 8). This means that the participant misunderstood the task instruction of recalling the final words and recalled whole sentences instead. After the first round of data cleaning, 252 participants were left in the sample. Further data cleaning was done in the analyses for each specific category learning task which I discussed below in the corresponding sections.

Descriptive Results of Predictors

A total of 177 participants were included in the analysis for the following descriptive statistics. The negative affect subscale of ATQ consisted of 25 items (α = .80), the effortful control subscale consisted of 19 items (α = .82), and the extraversion/surgency subscale consisted of 17 items (α = .75). These were highly consistent with the Crobach's Alpha values reported by Evans and Rotherbart (2007) which showed good internal consistency and high reliability. The score of each temperament trait for each participant was calculated by adding up the ratings on all items associated with this factor, then dividing the total number of items. Participants' negative affect scores ranged between 2.56 and 6.52 (*Median* = 4.52, *M* = 4.52, *sd* = 0.72). Their extraversion scores ranged between 2.59 and 7.24 (*Median* = 5.09, *M* = 5.01, *sd* = 0.83). The effortful control scores ranged between 2.00 and 5.84 (*Median* = 3.89, *M* = 3.89, *sd* = 0.78). Reading span scores ranged between 16 and 60 (*Median* = 48, *M* = 46.97, *sd* = 7.69).

3.3.3.1. CR Task

Additional Data Cleaning

A total of 18 additional participants were removed because they did not show any performance improvement throughout the CR task and had less than 60% performance in all learning phases. To detect performance improvement, I divided the total 200 trials into blocks of 50 and checked whether block 4 performance was higher than block 1. If this was not the case for certain participants, I then checked whether their best performing block had accuracy higher than 60%. Participants who did not satisfy both criteria were considered random responders and were excluded from further analyses in the CR task. After this round of data cleaning, 234 participants remained. **Table 3.8** shows the correlation matrix of the predictors based on the remaining participants' data.

Analysis of Overall Performance

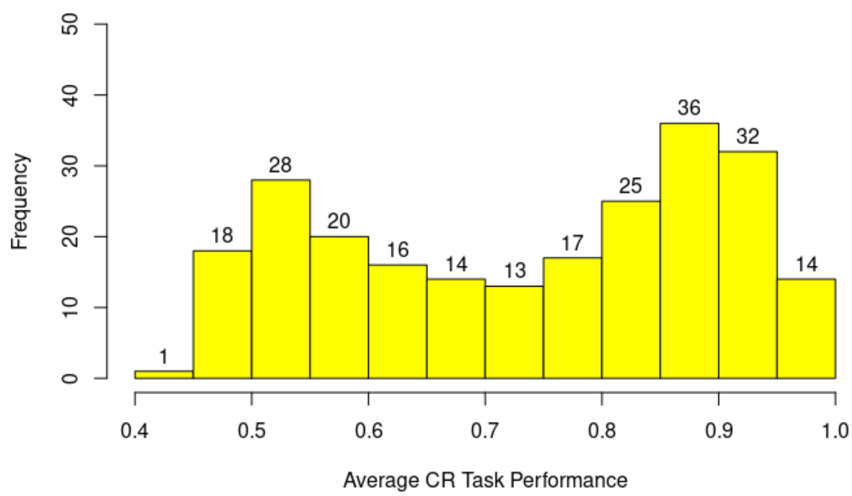
Descriptive Results of the Dependent Variable. The primary dependent variable was the overall category learning performance (*M* = 0.74, *SD* = 0.16). **Figure 3.21** shows the distribution of the overall average performance in the CR task based on all 234 participants' data. This bimodal distribution suggests there were two groups of participants, one group learned the task and the other group did not. An ANOVA test was conducted to detect whether performance

Table 3.8: Correlation matrix of the criteria and predictors of CR category learning in Experiment 2.

	Negative affect	Effortful control	Extraversion
Negative affect			
Effortful control	-0.466***		
Extraversion	-0.319***	0.029	
Reading span score	-0.033	-0.06	0.092

*** Correlation is significant at $p = 0.001$ level
$N = 234$

Figure 3.21. *Distribution of overall CR performance in Experiment 2*



Note. The numeric above each bar shows the number of participants who fell in each range. $N = 234$

Table 3.9: Frequency distribution of total participants, learners and proportion of non-learners in each CR condition

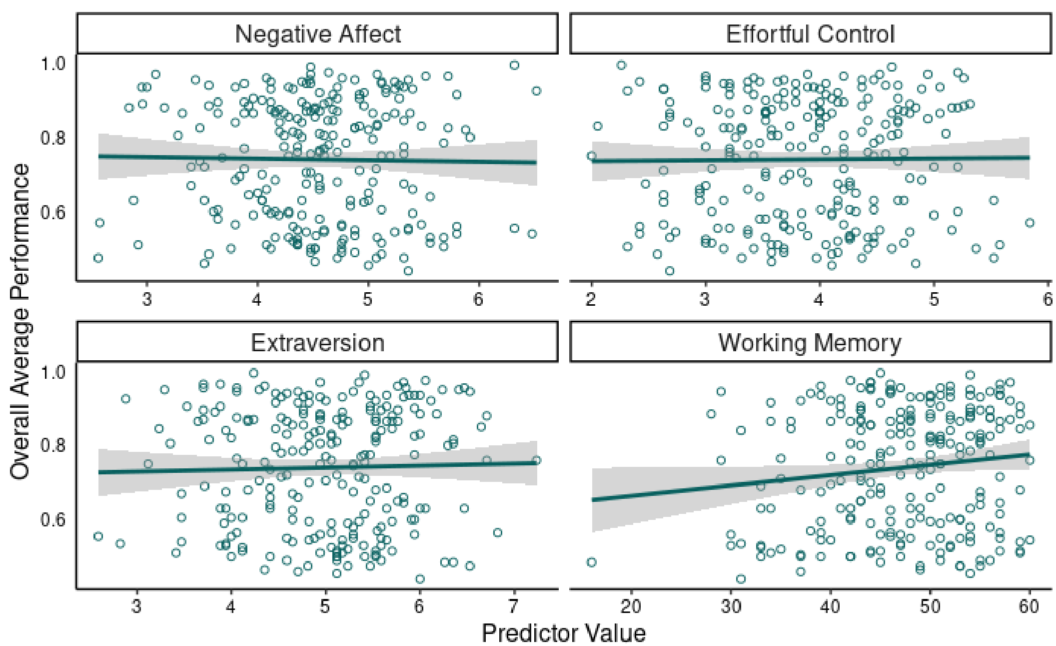
Predictor	All participants (N = 234)	Learners (N = 167)	% Non-learner
Condition 1	37	30	0.19
Condition 2	43	34	0.21
Condition 3	41	29	0.29
Condition 4	36	24	0.33
Condition 5	37	18	0.51
Condition 6	40	32	0.20

Note. Learners are participants who reached 10 consecutive correct within the 200 trials. %non-learner represents the number of non-learners divided by the total number of participants assigned to a specific condition. $N = 234$

differed across different CR conditions. Each CR condition had a different optimal conjunctive rule that was composed of different combinations of 2 features. See **Table 3.9** for the number of participants in each condition. There was no significant difference in performance between conditions, $F(5, 228) = 1.84$, $p = 0.11$. The rule conditions did not differ in perceived difficulty.

Multiple Regression Results Before conducting the multiple regression model, I examined the correlational relationship between each individual predictor and the overall average CR performance. This is visualized in **Figure 3.22** as scatterplots. Working memory had a weak correlation with overall CR performance: $r = 0.133$, $p = .042$; if the outlier on the lower left was removed, the correlation was no longer significant: $r = 0.11$, $p = .095$

Figure 3.22: *Scatter plot depicting the correlational relationship between each predictor and overall average CR performance in Experiment 2*



Note. Scatter plot for the temperament traits and working memory and their correlational relationship with overall average CR performance in Experiment 2. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), with a line of best fit (line) and 95% confidence interval (gray zone) for the respective measure.

The full model regression predicting overall average CR performance was significant, $F(12, 221) = 1.93$, $p = .032$. There was a significant main effect of effortful control [$\beta = -0.285$, $SE = 0.128$, $t(221) = -2.218$, $p = .028$]. Higher effortful control was associated with lower overall performance. The effect of negative affect was approaching significance [$\beta = -0.126$, $SE = 0.066$, $t(221) = -1.91$, $p = .057$]. The interaction effect between effortful control and negative affect was marginally significant [$\beta = 0.032$, $SE = 0.016$, $t(221) = 1.978$, $p = .049$]. Working memory was approaching significance [$\beta = 0.003$, $SE = 0.001$, $t(221) = 1.852$, $p = .065$]. See **Table 3.10** for more details, and these results can also be visualized in **Figure 3.23**.

Table 3.10: Full multiple regression model results predicting overall CR performance in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(221)	*p*
Negative Affect	-0.126	0.066	-0.552	0.288	-1.914	0.057
Extraversion	-0.116	0.067	-0.598	0.349	-1.715	0.088
Effortful Control	**-0.285**	**0.128**	**-1.361**	**0.614**	**-2.218**	**0.028**
Negative Affect x Effortful Control	**0.032**	**0.016**	**0.656**	**0.332**	**1.978**	**0.049**
Extraversion x Effortful Control	0.030	0.017	0.961	0.540	1.779	0.077
Working Memory	0.003	0.001	0.124	0.067	1.852	0.065
CR condition 2	-0.012	0.036	-0.072	0.222	-0.323	0.747
CR condition 3	0.034	0.036	0.211	0.223	0.947	0.345
CR condition 4	0.009	0.037	0.056	0.231	0.245	0.807
CR condition 5	-0.059	0.037	-0.364	0.230	-1.581	0.115
CR condition 6	0.066	0.037	0.407	0.231	1.764	0.079
Cat Order : II_first	0.003	0.001	0.124	0.067	1.852	0.065

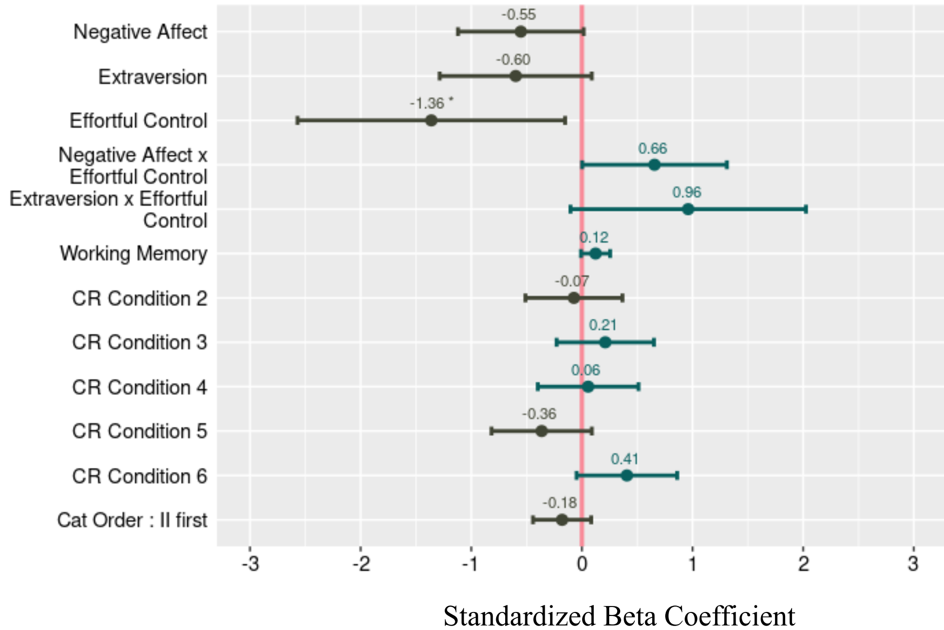
Note. Overall model was significant, $F(12, 221) = 1.93$, $p = .032$, $R^2 = 0.095$, $R^2_{adj} = 0.046$. $N = 234$. CR conditions represent different combinations of relevant conjunctive rule features. CR condition 1 was not shown in the table because it was treated as the intercept by the model. Cat order represents the order of category learning task, either CR task was learned first or II task was learned first. CR condition 1 was not shown in the table because it was treated as the intercept by the model.

The backwards elimination removed task order (i.e., whether learned CR first or II first) from the model while keeping the rest of the predictors. Overall model was significant, $F(11, 222) = 1.94$, $p = .036$. There was a significant main effect of effortful control [$\beta = -0.288$, $SE = 0.128$, $t(222) = -2.238$, $p = .026$]. Higher effortful control was associated with lower overall performance. There was also a significant main effect of working memory [$\beta = 0.003$, $SE = 0.001$, $t(222) = 2.07$, $p = .039$]. Higher working memory was associated with higher overall performance. The effect of negative affect was approaching significance [$\beta = -0.127$, $SE = 0.066$, $t(222) = -1.926$, $p = .055$]. The interaction effect between effortful control and negative affect was also approaching significance [$\beta = 0.031$, $SE = 0.016$, $t(222) = 1.94$, $p = .053$]. See **Table 3.11** for more details on the reduced model, and these results can also be visualized in **Figure 3.24**.

Analysis of the Rate of Learning

Descriptive Results of the Dependent Variable. The primary dependent variable was the number of trials each participant took to reach the criteria (i.e., 10 correct trials in a row; among learners: $M = 74.05$, $SD = 46.67$). **Figure 3.25** shows the distribution of trials to criterion (TTC) in the CR task where all 234 participants were included (participants who never got 10 correct in a row were assigned the maximum trial number 200).

Figure 3.23. *Standardized beta coefficient for full multiple regression models predicting overall average CR performance in Experiment 2*



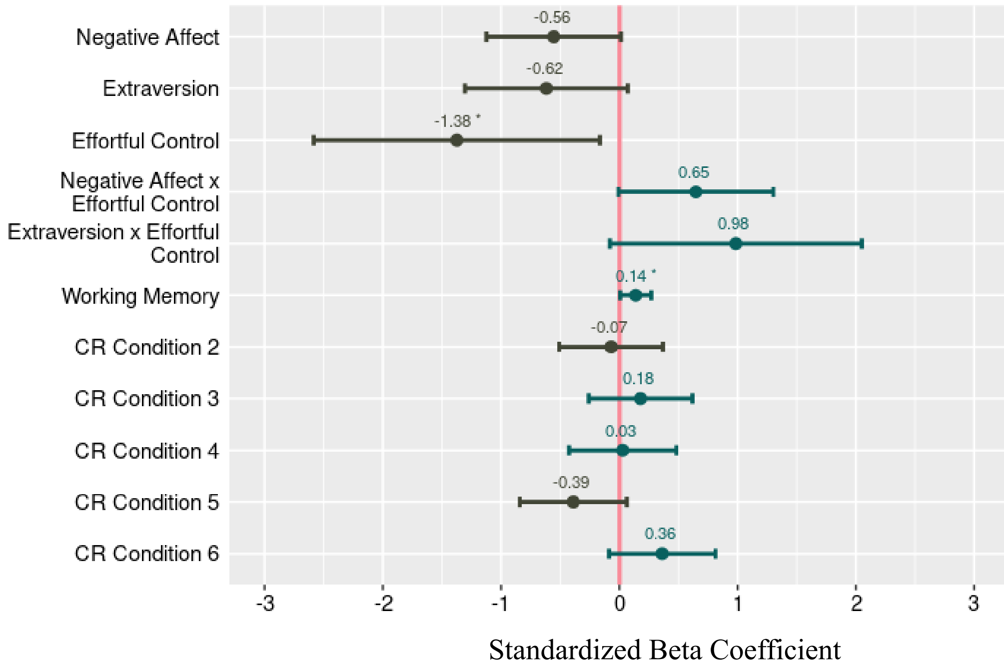
Note. Forest plot for the full multiple regression model. It depicts the model predicting overall average CR performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion. EC = effortful control. CR conditions represent different relevant conjunctive rule features. CR Condition 1 is not shown in the analysis results because it was used as the baseline.

Table 3.11: Reduced multiple regression model results predicting overall CR performance in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(222)	*p*
Negative Affect	-0.127	0.066	-0.556	0.289	-1.926	0.055
Extraversion	-0.119	0.067	-0.618	0.349	-1.771	0.078
Effortful Control	**-0.288**	**0.128**	**-1.375**	**0.615**	**-2.238**	**0.026**
Negative Affect:Effortful Control	0.031	0.016	0.646	0.332	1.943	0.053
Extraversion:Effortful Control	0.030	0.017	0.984	0.541	1.819	0.070
Working Memory	**0.003**	**0.001**	**0.137**	**0.066**	**2.072**	**0.039**
CR condition 2	-0.012	0.036	-0.071	0.223	-0.321	0.749
CR condition 3	0.029	0.036	0.177	0.222	0.798	0.426
CR condition 4	0.004	0.037	0.027	0.230	0.116	0.908
CR condition 5	-0.063	0.037	-0.391	0.229	-1.704	0.090
CR condition 6	0.058	0.037	0.361	0.229	1.581	0.115

Note. Overall model was significant, $F(11, 222) = 1.94$, $p = .036$, $R^2 = 0.087$, $R^2_{adj} = 0.042$. $N = 234$. CR conditions represent different combinations of relevant conjunctive rule features. CR condition 1 was not shown in the table because it was treated as the intercept by the model. CR condition 1 was not shown in the table because it was treated as the intercept by the model.

Figure 3.24. *Standardized beta coefficient for reduced multiple regression models predicting overall average CR performance in Experiment 2*



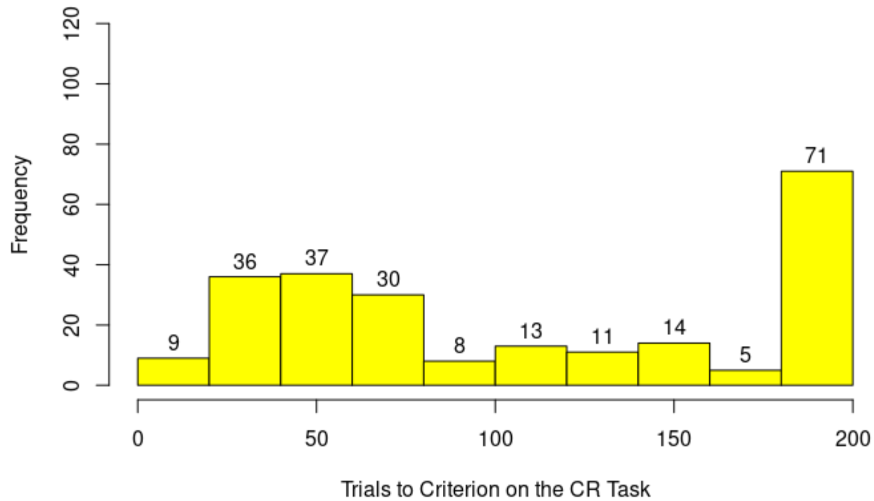
Note. Forest plot for the full multiple regression model. It depicts the model predicting overall average CR performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion. EC = effortful control. CR conditions represent different relevant conjunctive rule features. CR condition 1 was not shown in the table because it was treated as the intercept by the model.

An ANOVA test was conducted to detect whether TTC differed across different CR conditions. See **Table 3.9** for learner and non-learner count in each CR condition. There was a significant effect of CR conditions, $F(5, 161) = 2.34$, $p = 0.044$. The only significant difference in TTC was detected between condition 3 and 2, see **Figure 3.26** for more details.

Multiple Regression Results. Before conducting the multiple regression model, I examined the correlational relationship between each individual predictor and the TTC on the CR task (based on learner-only data). This is visualized in **Figure 3.27** as scatterplots.

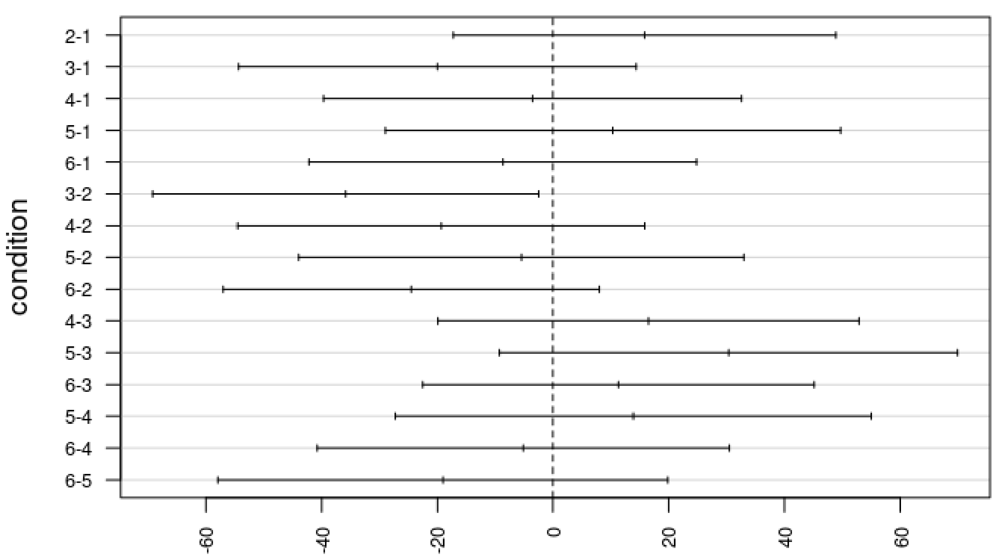
Only participants who got 10 correct in a row ($N = 167$) were included in the regression analysis because it would be unsound to arbitrarily assign a TTC value for non-learners. The full model regression predicting TTC on the CR task was not significant, $F(12, 154) = 1.47$, $p = .14$. None of the predictors was significant in the full model, see **Table 3.12** for more details. These results can also be visualized in **Figure 3.28**.

Figure 3.25: *Distribution of TTC on the CR Task in Experiment 2*



Note. Participants who took exactly 200 trials to complete the task were non-learners. The numeric above each bar shows the number of participants who fell in each range.

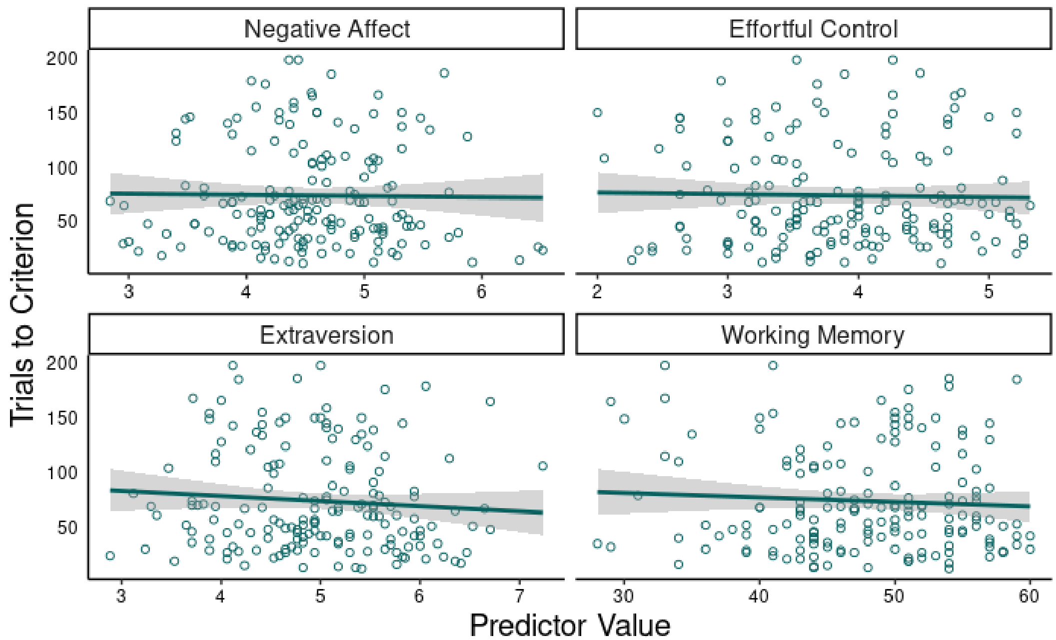
Figure 3.26. *Tukey's HSD multiple comparisons of TTC between CR condition with 95% confidence interval*



TTC Differences Between CR Conditions

Note. This plot depicts the multiple comparisons between TTC in any 2 conditions for the CR task in Experiment 2. The x-axis represents the mean differences that were found between the pairs. The extended lines show the 95% confidence intervals. Confidence interval crosses 0 means the difference between conditions TTC is not significant at $p = .05$.

Figure 3.27: *Scatter plot depicting the correlational relationship between each predictor and TTC on the CR task in Experiment 2*



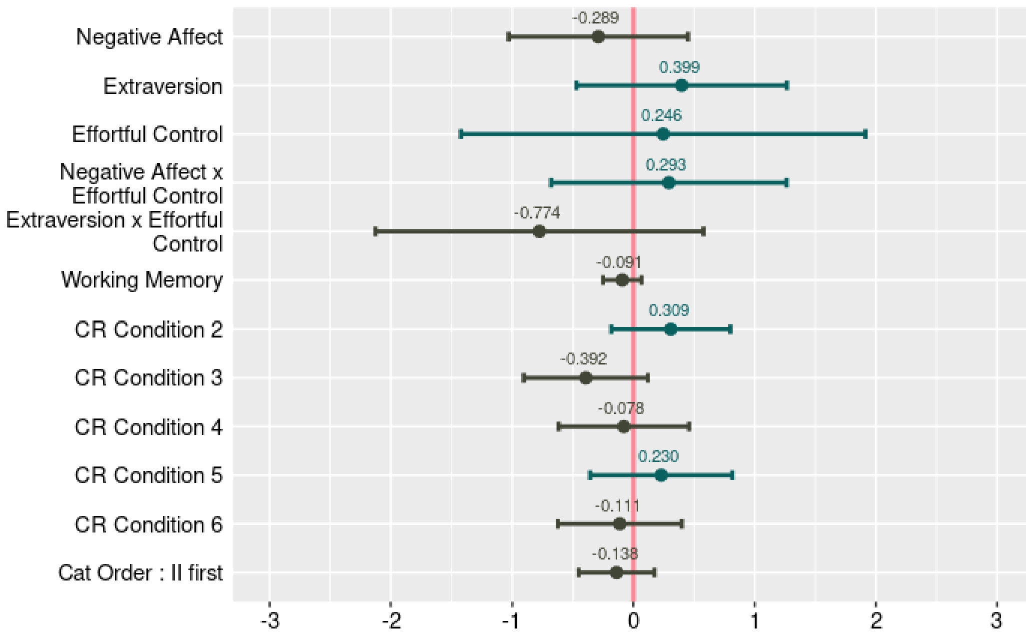
Note. Scatter plot for the temperament traits and working memory and their correlational relationship with TTC on the CR task in Experiment 2. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), with a line of best fit (line) and 95% confidence interval (gray zone) for the respective measure.

Table 3.12: Full multiple regression model results predicting TTC on the CR task in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(154)	*p*
Negative affect	-19.738	25.580	-0.289	0.374	-0.772	0.442
Extraversion	22.453	24.730	0.399	0.439	0.908	0.365
Effortful control	14.919	51.209	0.246	0.844	0.291	0.771
Negative affect:Effortful control	3.871	6.496	0.293	0.491	0.596	0.552
Extraversion:Effortful control	-6.973	6.168	-0.774	0.685	-1.131	0.260
Working Memory	-0.595	0.523	-0.091	0.080	-1.136	0.258
CR condition 2	14.427	11.598	0.309	0.248	1.244	0.215
CR condition 3	-18.299	12.087	-0.392	0.259	-1.514	0.132
CR condition 4	-3.644	12.706	-0.078	0.272	-0.287	0.775
CR condition 5	10.723	13.846	0.230	0.297	0.774	0.440
CR condition 6	-5.194	12.072	-0.111	0.259	-0.430	0.668
Cat order: II first	-6.455	7.383	-0.138	0.158	-0.874	0.383

Note. Overall model was not significant, $F(12, 154) = 1.47$, $p = .14$, $R^2 = 0.10$, $R^2_{adj} = 0.03$. $N = 167$. CR conditions represent different combinations of relevant conjunctive rule features. CR condition 1 was not shown in the table because it was treated as the intercept by the model.

Figure 3.28: *Standardized beta coefficient for full multiple regression model predicting TTC on the CR task in Experiment 2.*



Standardized Beta Coefficient

Note. Forest plot for the full multiple regression model. It depicts the full model predicting TTC on the CR task. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion. CR condition 1 was not shown in the table because it was treated as the intercept by the model.

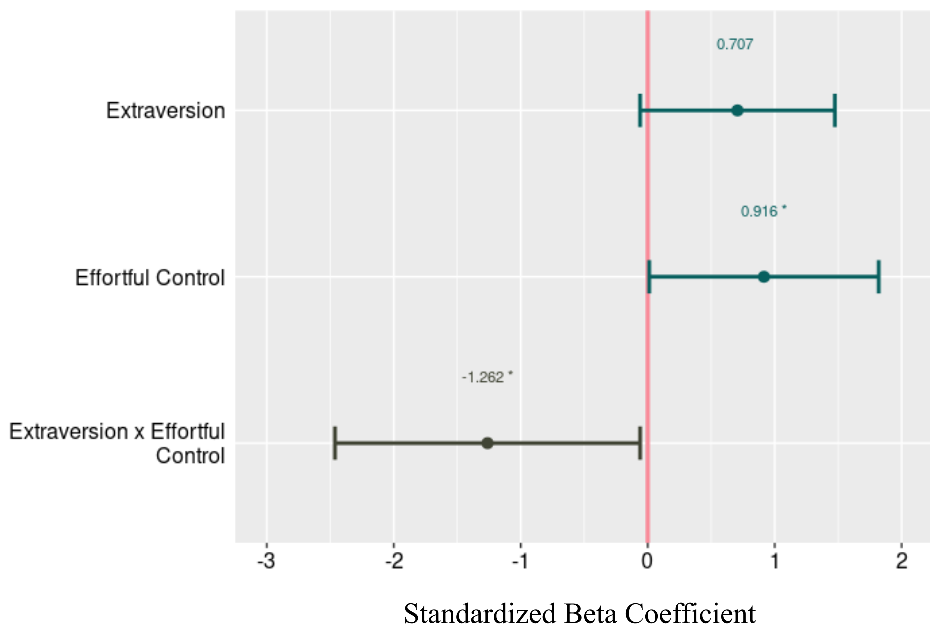
The reduced model regression predicting TTC on the CR task was not significant, $F(3, 163) = 1.85$, $p = .14$. See **Table 3.13** for model statistics for the reduced model and these results can also be visualized in **Figure 3.29**. There was no significant effect of extraversion/surgency [$\beta = 38.83$, $SE = 21.89$ $t(163) = 1.82$, $p = .071$] on learning rate in the CR task. The effect of effortful control was marginally significant [$\beta = 55.53$, $SE = 27.75$, $t(163) = 2.00$ $p = .047$]. There was a significant interaction effect between effortful control and extraversion/surgency [$\beta = -11.37$, $SE = 5.48$, $t(163) = -2.07$, $p = .040$]. Higher effortful control reduced the effect of extraversion/surgency on slowing down learning.

Table 3.13: Reduced multiple regression model results predicting TTC on the CR task in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(163)	*p*
Extraversion	39.825	21.886	0.707	0.389	1.820	0.071
Effortful control	**55.534**	**27.751**	**0.916**	**0.458**	**2.001**	**0.047**
Extraversion:Effortful control	**-11.365**	**5.481**	**-1.262**	**0.608**	**-2.073**	**0.040**

Note. Overall model was not significant, $F(3, 163) = 1.85$, $p = .14$, $R^2 = 0.033$, $R^2_{adj} = 0.015$. $N = 167$.

Figure 3.29: *Standardized beta coefficient for reduced multiple regression model predicting TTC on the CR task in Experiment 2*



Note. Forest plot for the reduced multiple regression model. It depicts the reduced model predicting TTC on the CR task. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion.

Since about ⅓ of participants did not reach the learning criterion of 10 consecutive correct responses. Independent-samples t-tests were conducted to assess the trait differences between learners and non-learners. The two groups did not differ on extraversion/surgency, $t(118.11) = -0.83$, $p = .41$; negative affect, $t(108.86) = 0.011$, $p = .0.99$; effortful control, $t(119.38) = -0.50$, $p = .62$; or working memory $t(102.79) = 1.52$, $p = .13$.

3.3.3.2. II Task

Additional Data Cleaning

A total of 28 additional participants were removed because they did not show any performance improvement throughout the II task and had less than 60% performance in all learning phases. The steps taken to remove these participants were identical to those done in the CR task. Participants who did not satisfy both criteria were considered random responders and were excluded from further analyses in the CR task. After this round of data cleaning, 224 participants remained. **Table 3.14** shows the correlation matrix of the predictors based on the remaining participants' data.

Table 3.14: Correlation matrix of the criteria and predictors of II category learning in Experiment 2

	Negative affect	Effortful control	Extraversion
Negative affect			
Effortful control	-0.474***		
Extraversion	-0.367***	0.092	
Reading span score	-0.015	-0.119	0.116

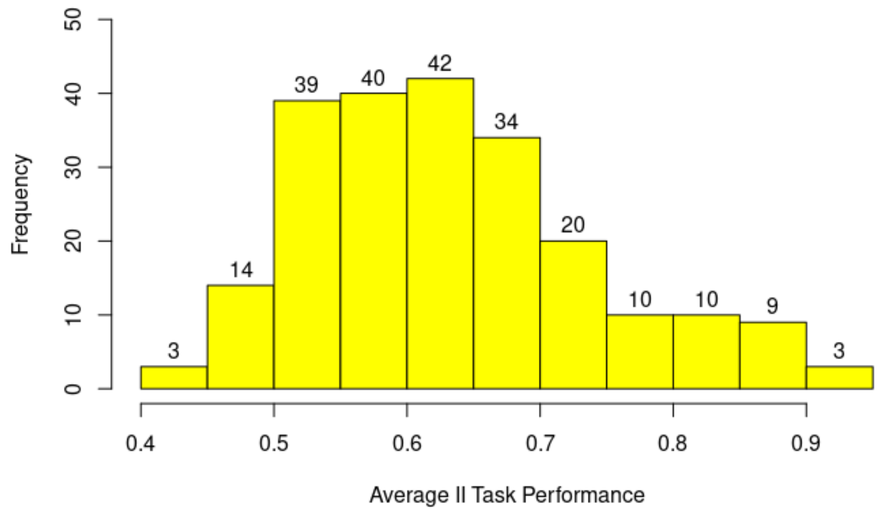
*** Correlation is significant at $p = 0.001$ level
$N = 224$

Analysis of Overall Performance

Descriptive Results of the Dependent Variable. The primary dependent variable was the overall category learning performance ($M = 0.63$, $SD = 0.11$). **Figure 3.30** shows the distribution of the overall average performance in the II task based on all 224 participants' data. This right skewed unimodal distribution suggests that the majority of participants had low overall performance. An ANOVA test was conducted to detect whether performance differed across different II conditions. See **Table 3.15** for the number of participants in each condition. There was no significant difference in performance between conditions, $F(3, 220) = 0.55$, $p = 0.65$.

Multiple Regression Results. Before conducting the multiple regression model, I examined the correlational relationship between each individual predictor and the overall average II performance. This is visualized in **Figure 3.31** as scatterplots.

Figure 3.30. *Distribution of overall II performance in Experiment 2*



Note. The numeric above each bar shows the number of participants who fell in each range.

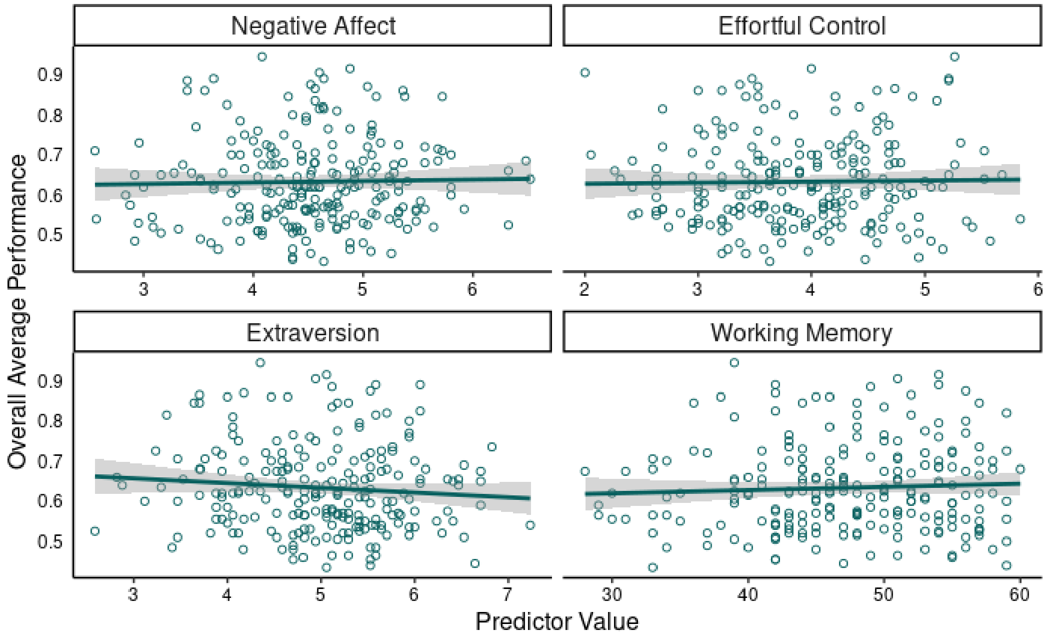
Table 3.15: Frequency distribution of total participants, learners and proportion of non-learners in each II condition

Predictor	All participants (*N* = 224)	Learners (*N* = 122)	% Non-learner
Condition 1	55	28	0.49
Condition 2	61	38	0.38
Condition 3	52	31	0.40
Condition 4	56	25	0.55

Note. Learners are participants who reached 10 consecutive correct within the 200 trials. %non-learner represents the number of non-learners divided by the total number of participants assigned to a specific condition. *N* = 224

The full model regression predicting overall average II performance was not significant, $F(10, 213) = 1.39$, $p = .19$. The main effect of extraversion/surgency was approaching significance, [$\beta = -0.097$, $SE = 0.049$, $t(213) = -1.97$, $p = .050$]. There was a significant main effect of effortful control [$\beta = -0.219$, $SE = 0.095$, $t(213) = -2.314$, $p = .022$] and negative affect [$\beta = -0.108$, $SE = 0.047$, $t(213) = -2.291$, $p = .023$]. Higher effortful control or higher negative affect was associated with lower overall performance. The interaction effect between effortful control and negative affect was also significant [$\beta = 0.027$, $SE = 0.011$, $t(213) = 2.40$, $p = .017$]. Higher effortful control increased the effect of negative affect on lowering overall performance. See **Table 3.16** for more details, and these results can also be visualized in **Figure 3.32**.

Figure 3.31: *Scatter plot depicting the correlational relationship between each predictor and overall average II performance in Experiment 2.*



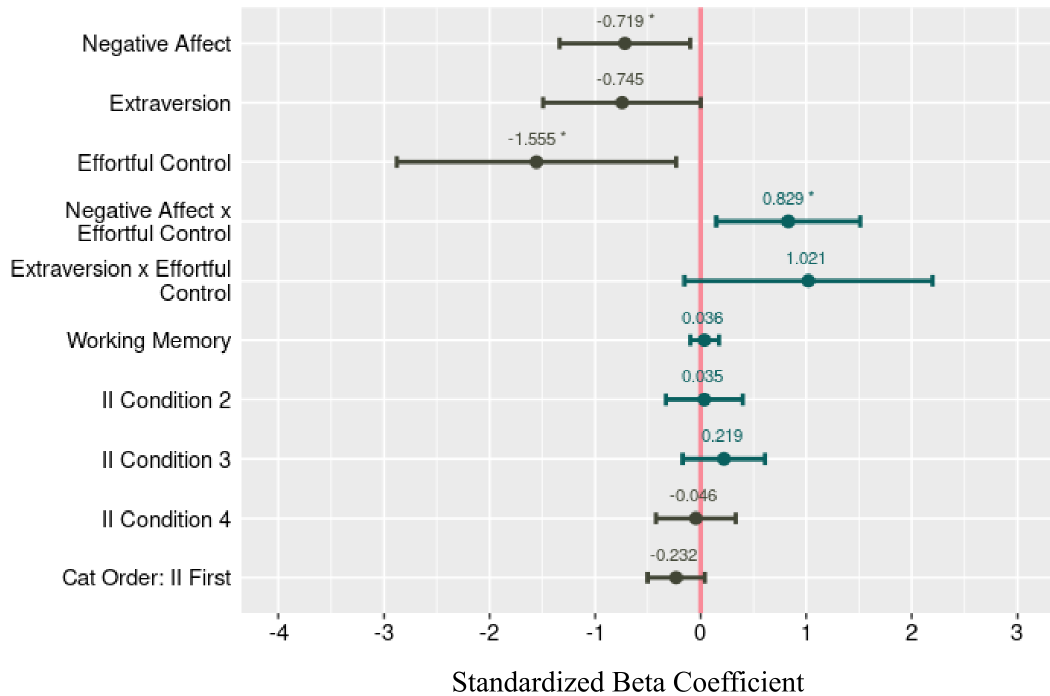
Note. Scatter plot for the temperament traits and working memory and their correlational relationship with overall average II performance in Experiment 2. For each predictor, the x-axis depicts that actual raw score for the respective measure. Individual participants are depicted (dots), with a line of best fit (line) and 95% confidence interval (gray zone) for the respective measure.

Table 3.16: Full multiple regression model results predicting overall II performance in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(213)	*p*
Negative affect	**-0.108**	**0.047**	**-0.719**	**0.314**	**-2.291**	**0.023**
Extraversion	-0.097	0.049	-0.745	0.378	-1.969	0.050
Effortful control	**-0.219**	**0.095**	**-1.555**	**0.672**	**-2.314**	**0.022**
Negative affect:Effortful control	**0.027**	**0.011**	**0.829**	**0.346**	**2.397**	**0.017**
Extraversion:Effortful control	0.021	0.012	1.021	0.596	1.712	0.088
Rspan score	0.001	0.001	0.036	0.069	0.527	0.599
II condition 2	0.004	0.020	0.035	0.185	0.192	0.848
II condition 3	0.024	0.022	0.219	0.198	1.107	0.269
II condition 4	-0.005	0.021	-0.046	0.192	-0.241	0.810
Cat order: II first	-0.025	0.015	-0.232	0.138	-1.680	0.094

Note. Overall model was not significant, $F(10, 213) = 1.39$, $p = .19$, $R^2 = 0.061$ $R^2_{adj} = 0.017$. $N = 224$. II conditions represent different combinations of category relevant features. II condition 1 was not shown in the table because it was treated as the intercept by the model.

Figure 3.32: *Standardized beta coefficient for full multiple regression models predicting overall average II performance in Experiment 2*



Note. Forest plot for the full multiple regression model. It depicts the model predicting overall average II performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion. EC = effortful control. II conditions represent different relevant conjunctive rule features. Cat order = the order of category learning tasks, either CR first or II first. II condition 1 was not shown in the table because it was treated as the intercept by the model.

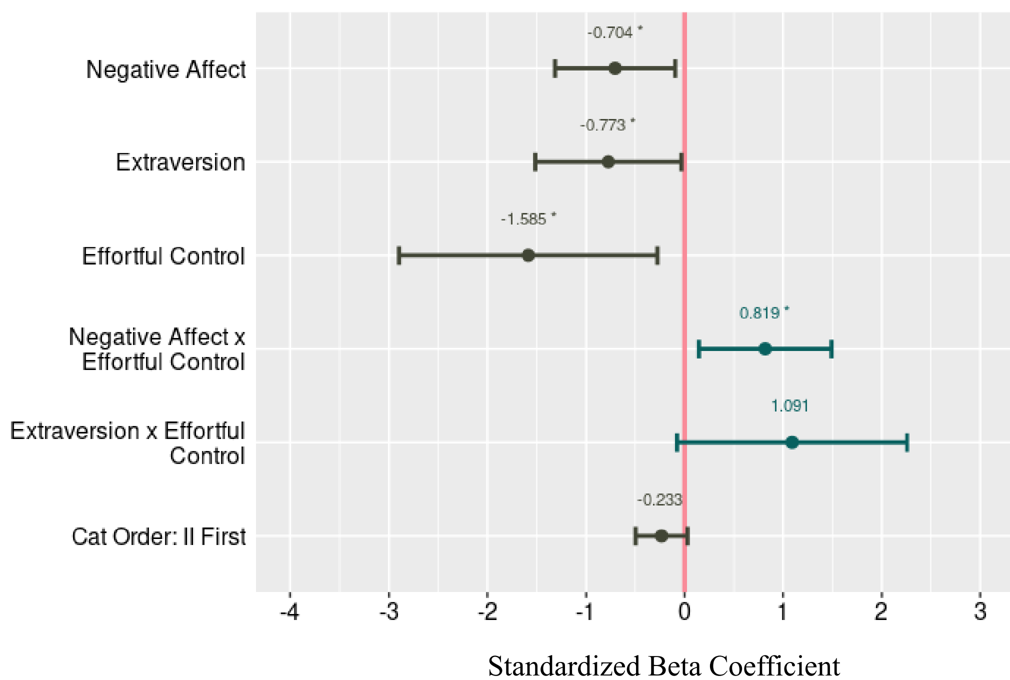
The backwards elimination removed II condition (i.e., different combination of relevant category features) and working memory from the model while keeping the rest of the predictors. Overall model was not significant, $F(6, 217) = 1.93$, $p = .077$. There was a significant main effect of effortful control [$\beta = -0.223$, $SE = 0.094$, $t(217) = -2.384$, $p = .018$]. Higher effortful control was associated with lower overall performance. There was also a significant main effect of negative affect [$\beta = -0.105$, $SE = 0.046$, $t(217) = -2.27$, $p = .024$]. Higher negative affect was associated with lower overall performance. The effect of extraversion was marginally significant [$\beta = -0.10$, $SE = 0.049$, $t(217) = -2.055$, $p = .041$]. The interaction effect between effortful control and negative affect was also significant [$\beta = 0.027$, $SE = 0.011$, $t(217) = 2.40$, $p = .017$]. See **Table 3.17** for more details on the reduced model, and these results can also be visualized in **Figure 3.33**.

Table 3.17: Reduced multiple regression model results predicting overall II performance in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(217)	*p*
Negative affect	**-0.105**	**0.046**	**-0.704**	**0.310**	**-2.274**	**0.024**
Extraversion	**-0.100**	**0.049**	**-0.773**	**0.376**	**-2.055**	**0.041**
Effortful control	**-0.223**	**0.094**	**-1.585**	**0.665**	**-2.384**	**0.018**
Negative affect:Effortful control	**0.027**	**0.011**	**0.819**	**0.341**	**2.402**	**0.017**
Extraversion:Effortful control	0.022	0.012	1.091	0.592	1.844	0.067
Cat order: II first	-0.026	0.015	-0.233	0.133	-1.753	0.081

Note. Overall model was not significant, $F(6, 217) = 1.93$, $p = .077$, $R^2 = 0.051$, $R^2_{adj} = 0.024$. $N = 224$.

Figure 3.33. *Standardized beta coefficient for reduced multiple regression models predicting overall average II performance in Experiment 2*



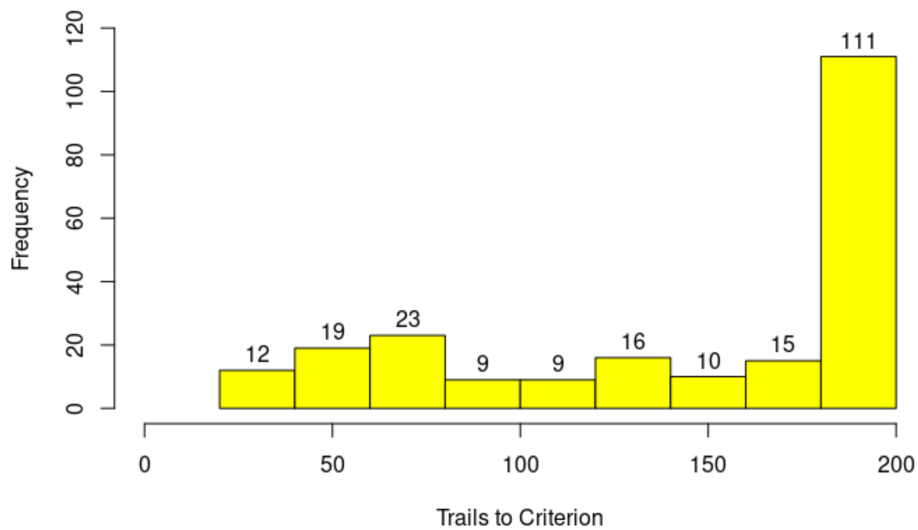
Note. Forest plot for the full multiple regression model. It depicts the model predicting overall average II performance. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion. EC = effortful control. Cat order = the order of category learning tasks, either CR first or II first.

Analysis of the Rate of Learning

Descriptive Results of the Dependent Variable. The primary dependent variable was the number of trials each participant took to reach the criteria (i.e., 10 correct trials in a row; among learners: among learners: *M* = 102.73, *SD* = 50.92). **Figure 3.34** shows the distribution of trials to criterion (TTC) in the II task where all 224 participants were included (participants who never got 10 correct in a row were assigned the maximum trial number 200).

An ANOVA test was conducted to detect whether TTC differed across different II conditions. See Table 3.15 for learner and non-learner counts in each II condition. Around 40% - 55% of participants failed to reach criterion in each of the conditions. There was a significant difference in TTC between II conditions, $F(3, 118) = 2.89$, $p = 0.039$. The only significant difference in TTC was detected between condition 3 and 1, see **Figure 3.35** for more details.

Figure 3.34: *Distribution of TTC on the II Task in Experiment 2*

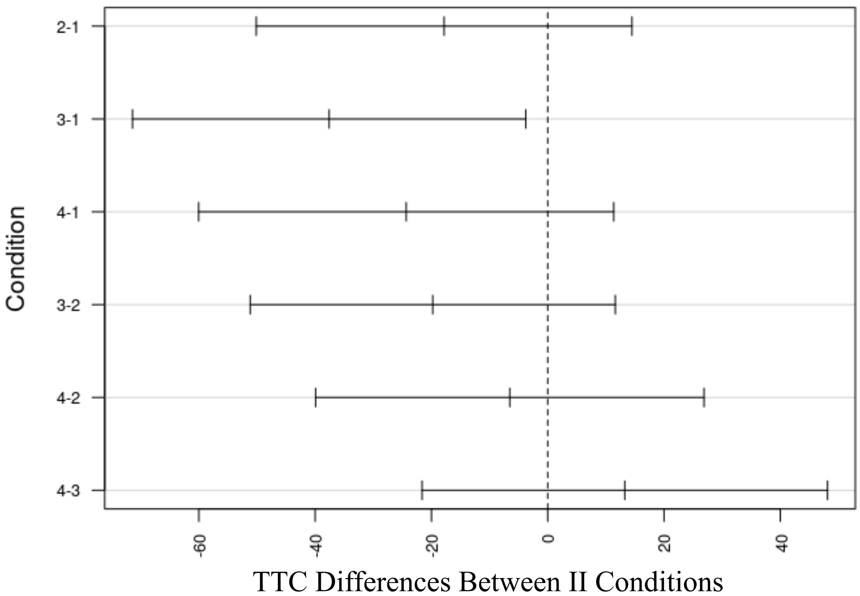


Note. Participants who took exactly 200 trials to complete the task were non-learners. The numeric above each bar shows the number of participants who fell in each range.

Multiple Regression Results. Before conducting the multiple regression model, I examined the correlational relationship between each individual predictor and the TTC on the II task (based on learner-only data). This is visualized in **Figure 3.36** as scatterplots.

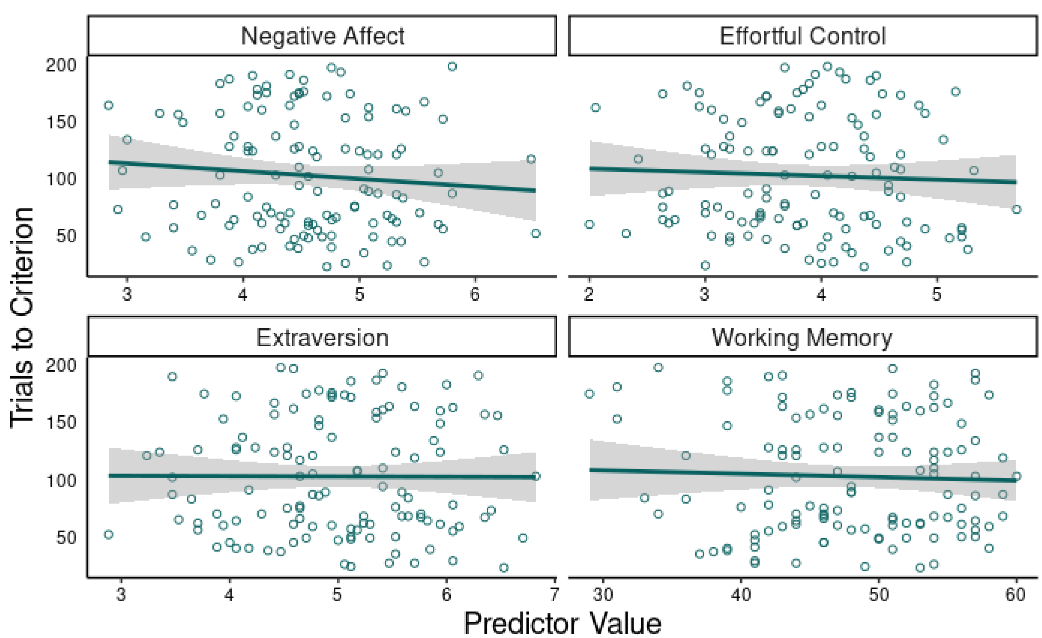
Only participants who got 10 correct in a row ($N = 122$) were included in the regression analysis because it would be unsound to arbitrarily assign a TTC value for non-learners. The full model regression predicting TTC on the II task was not significant, $F(10, 111) = 1.42$, $p = .18$. None of the theoretical predictors was significant in the full model, see **Table 3.18** for more details. These results can also be visualized in **Figure 3.37**.

Figure 3.35. *Tukey's HSD multiple comparisons of TTC between II condition with 95% confidence interval*



Note. This plot depicts the multiple comparisons between TTC in any 2 conditions for the II task in Experiment 2. The x-axis represents the mean differences that were found between the pairs. The extended lines show the 95% confidence intervals. C

Figure 3.36: *Scatter plot depicting the correlational relationship between each predictor and TTC on the II task in Experiment 2.*



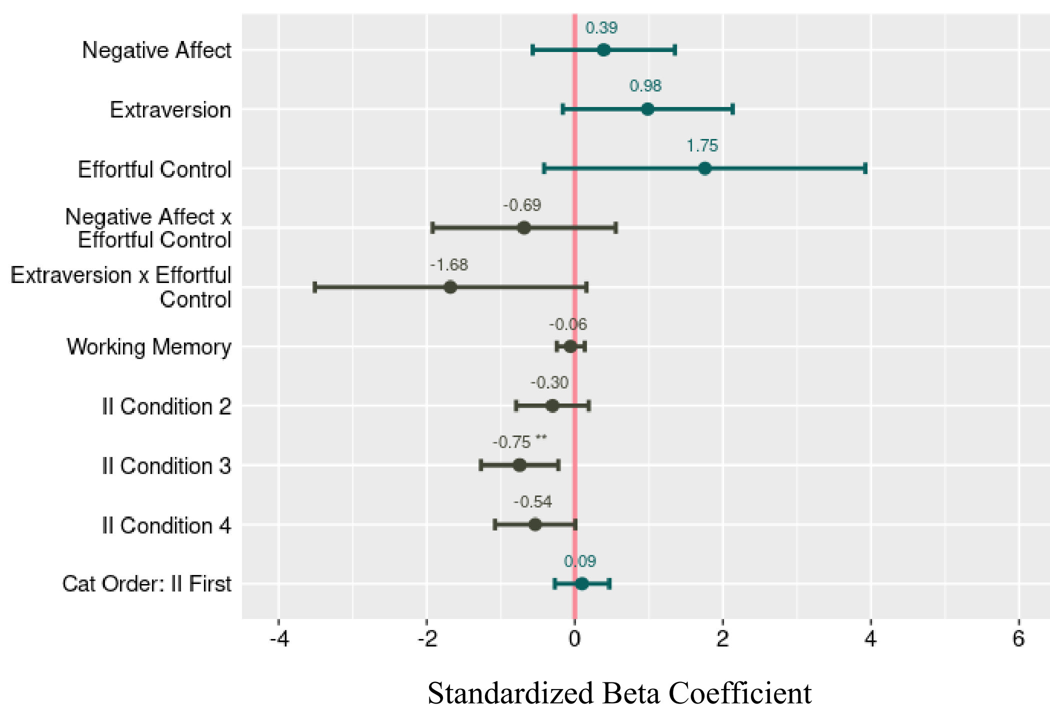
Note. This plot depicts the multiple comparisons between TTC in any 2 conditions for the II task in Experiment 2. The x-axis represents the mean differences that were found between the pairs. The extended lines show the 95% confidence intervals. Confidence interval crosses 0 means the difference between conditions TTC is not significant at $p = .05$.

Table 3.18: Full multiple regression model results predicting TTC on the II task in Experiment 2

Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(111)	p
Negative Affect	27.826	34.779	0.387	0.484	0.800	0.425
Extraversion	59.153	34.893	0.981	0.578	1.695	0.093
Effortful Control	117.507	73.354	1.753	1.095	1.602	0.112
Negative Affect x Effortful Control	-9.468	8.582	-0.689	0.624	-1.103	0.272
Extraversion x Effortful Control	-15.856	8.728	-1.682	0.926	-1.817	0.072
Rspan Score	-0.432	0.692	-0.059	0.095	-0.624	0.534
II Condition 2	-15.509	12.544	-0.305	0.246	-1.236	0.219
II Condition 3	**-38.089**	**13.391**	**-0.748**	**0.263**	**-2.844**	**0.005**
II Condition 4	-27.386	14.012	-0.538	0.275	-1.954	0.053
Cat Order: II First	4.775	9.474	0.094	0.186	0.504	0.615

Note. Overall model was not significant, $F(10, 111) = 1.42$, $p = .18$, $R^2 = 0.11$, $R^2_{adj} = 0.03$. $N = 122$. II conditions represent different combinations of relevant features. II condition 1 was not shown in the table because it was treated as the intercept by the model.

Figure 3.37: *Standardized beta coefficient for full multiple regression model predicting TTC on the II task in Experiment 2.*



Note. Forest plot for the full multiple regression model. It depicts the reduced model predicting TTC on the II task. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion. II condition 1 was not shown in the table because it was treated as the intercept by the model.

See **Table 3.19** for model statistics for the reduced model and these results can also be visualized in **Figure 3.38**. The overall reduced model regression predicting TTC on the II task was not significant, $F(6, 115) = 1.80$, $p = .11$. The only significant effect was II condition. Results suggested that participants took significantly lesser trials to reach the criterion in condition 3 than condition 1. As we can see in Table 3.15 that 40% of participants failed to reach criterion in condition 3 compared to 49% in condition 1. Having a higher proportion of non-learners accompanied by significantly higher TTC suggested that condition 1 was more difficult to learn than condition 3, this may be a limitation in the II task design.

Table 3.19: Reduced multiple regression model results predicting TTC on the II task in Experiment 2

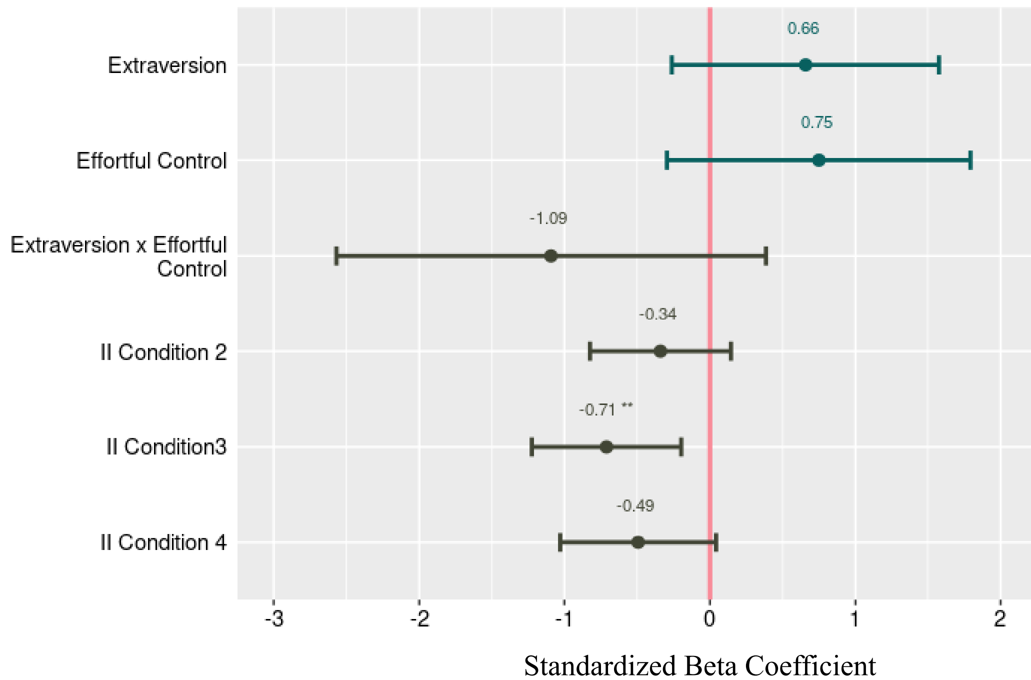
Predictor	ß	$SE_{ß}$	Std. ß	Std.$SE_{ß}$	t(163)	*p*
Extraversion	39.639	27.992	0.657	0.464	1.416	0.159
Effortful_control	50.179	35.329	0.749	0.527	1.420	0.158
Extraversion:Effortful_control	-10.293	7.028	-1.092	0.746	-1.465	0.146
II condition 2	-17.314	12.445	-0.340	0.244	-1.391	0.167
II condition 3	**-36.178**	**13.189**	**-0.710**	**0.259**	**-2.743**	**0.007**
II condition 4	-25.118	13.763	-0.493	0.270	-1.825	0.071

Note. Overall model was not significant, $F(6, 115) = 1.80$, $p = .11$, $R^2 = 0.086$, $R^2_{adj} = 0.038$. $N = 122$. II condition 1 was not shown in the table because it was treated as the intercept by the model.

Since about ½ of participants did not reach the learning criterion of 10 consecutive correct responses. Independent-samples t-tests were conducted to assess the trait differences between learners and non-learners. The two groups did not differ on extraversion/surgency, $t(214.76) = -0.26$, $p = .79$; negative affect, $t(209.65) = 0.89$, $p = .0.38$; or effortful control, $t(211.14) = -0.92$, $p = .36$. Learners had marginally better working memory, $t(209.18) = 1.93$, $p = .055$, but this was not statistically significant.

There were 128 participants who learned the CR task faster than II task, and 52 participants who learned the II task faster than CR task, and the remaining 44 participants failed to reach the criterion on either task. I compared the II faster and CR faster groups on each trait predictors. The two groups did not differ on extraversion/surgency, $t(100.06) = 0.079$, $p = .94$; negative affect, $t(100.2) = 0.21$, $p = .83$; effortful control, $t(90.28) = -0.09$, $p = .93$; or working memory, $t(102.29) = 0.22$, $p = .82$.

Figure 3.38: *Standardized beta coefficient for reduced multiple regression model predicting TTC on the II task in Experiment 2.*



Note. Forest plot for the reduced multiple regression model. It depicts the full model predicting TTC on the II task. Standardized beta coefficients (dots) and the 95 % confidence interval (whiskers) are shown for each model. Vertical line represents the neutral point or no relationship between the predictor and the criterion.

3.3.4. Interim Discussion

Experiment 2 examined the effects of temperament traits on learning CR and II categorization tasks. Individuals with lower negative affect tended to have higher overall II performance, this result is in line with the claims of affect-as-information framework. This theory proposes that high negative affect leads to explicit analytical processing, which is incongruent with the optimal strategy required to learn the II task. However, the lack of extraversion effect on CR task and negative effect on II task performance did not support either the dopaminergic theory or affect-as-information framework. The dopaminergic theory contends that higher extraversion leads to higher verbal fluency and better feedback processing, therefore should be beneficial to both types of category learning. The affect-as-information framework proposes that high extraversion is associated with broad and implicit processing, which is congruent with II task learning and incongruent with CR task learning. Neither theory can be used to explain the absence or negative extraversion effect.

None of the temperament traits was found to be significantly predictive of II strategy learning rate. The significant predictors of CR strategy learning rate were effortful control and the interaction between extraversion and effortful control, but they should be interpreted with caution due to the marginal nature of these significance.

Contrary to the prediction, temperamental effortful control was associated with lower overall performance on both the CR and II tasks. The modulating effect of effortful control on affective temperament was also found to be inconsistent across tasks. Interestingly, working memory was only significantly associated with better overall CR performance in Experiment 2; recall that this relationship only was seen in the II task in Experiment 1.

One limitation in Experiment 2 was the potential of certain category conditions being more difficult to learn than another condition. This could be due to a specific feature combination having higher overall saliency compared to other combinations, may that be due to feature locations or size. However, there was no difference in overall performance across the conditions in either the CR or II task. This difference was only seen between one pair of conditions in each task during multiple comparisons of TTC. Specifically between condition 3 and 2 for CR task, and between condition 3 and 1 for II task.

3.4. General Discussion

Two experiments were conducted to determine whether temperament traits and working memory are predictive of people's ability to learn the rule-based and similarity-based categorization tasks. Two theories of transient affect were used to predict affective temperament trait effects. Dopaminergic theory proposes that individuals with higher extraversion would have an advantage in learning both types of categories (Ashby et al., 1998, 1999). According to this theory, cognitive flexibility and verbal fluency are related to rule selection and rule switching (Owen et al., 1993), which are beneficial to rule-based category learning. The dopaminergic theory further postulates that striatal dopamine is critical in mediating feedback in procedural learning (Ashby et al., 2007). Positive affect facilitates similarity-based tasks through projecting dopamine into the striatum, a critical region involved in this type of processing. On the other hand, affect-as-information framework contends that higher extraversion would only be associated with an advantage in similarity-based category learning, whereas higher negative affect would facilitate rule-based category learning (Gasper & Clore, 2000; Schwarz & Clore, 1983; Wyer et al., 1999). According to this theory, positive affect signifies a safe environment and promotes a focus on internally accessible information, and negative affect signifies problematic environment and promotes a focus on gathering external information (Clore et al., 2001). Internally focused approaches tend to be intuitive and implicit, while externally focused approaches tend to be analytical and explicit. Implicit processing elicited by positive affect is congruent with the optimal strategy required by the similarity-based task, while analytical processing elicited by negative affect is congruent with the optimal strategy required by rule-based tasks. Temperamental effortful control and working memory concerns the executive attention system, and higher executive attention has been associated with better rule-based and similarity-based category learning (Deng & Sloutsky, 2016; Miles & Minda, 2009; Davidson et al., 2003; Filoteo et al., 2010; May & Hasher, 1998; Wang et al., 2015; West, 1999; Williams et al., 1999; Deng & Sloutsky, 2016; Miles & Minda, 2009).

3.4.1. Summary of Results

Experiment 1 did not support either theory of transient affect. There was no relationship between affective temperament traits and overall learning performance on either type of categories. Experiment 1 also did not show an effect of temperamental effortful control, thus was not aligned with the hypothesis based on executive attention effect. Higher working memory was significantly predictive of only overall II performance but not overall CR performance, partially agreeing with the hypothesis that it would have a general facilitatory effect.

The II task results from Experiment 2 supported the affect-as-information hypothesis where higher negative affect was associated with lower overall performance due to the incongruency between II task demand and cognitive processing mode associated with high negative affect. However, there was no affective temperament effect on CR task or on II task optimal strategy learning rate. Results relating to temperamental effortful control in Experiment 2 were not supporting the hypothesis based on executive attention effect. It was hypothesized that effortful control should be facilitatory to both types of category learning. Effortful control was found to be negatively correlated with overall performance on both the CR and II tasks, and positively correlated with TTC on the CR task. It seems to have facilitated CR strategy learning by reducing the effect of extraversion/surgency in slowing down the process. However, this interaction effect was marginally significant ($p = 0.040$), and the main effect of effortful control in this analysis suggested a slowing down effect. Therefore the interaction effect should be interpreted with caution. Effortful control was also found to further lower the overall performance on II task on top of the effect of negative affect, contrary to the hypothesis that it should neutralize the biased tendency elicited by affective trait. Working memory as measured by Rspan task significantly predicted only overall CR performance in Experiment 2, partially agreeing with the hypothesis that it would have a general facilitatory effect.

Next, instead of looking at each experiment's results separately, I interpret findings from the two studies side-by-side and discuss the predictors in two sections: affective temperament and executive attention.

3.4.2. Affective Temperament

In Experiment 1, none of the affective temperament traits was predictive of overall performance on either CR or II task. Strategy analysis suggested that extraversion was significantly predictive of more likelihood to use single dimensional rule strategy compared to random strategy. In Experiment 2, negative affect and extraversion were both significantly predictive of lower overall II performance. Neither of the affective temperament traits was significant in the analyses of optimal strategy learning rate. These inconsistent results may be attributed to the timing of data collection. Data for both studies happened to be collected at especially trying times during the pandemic.

Experiment 1 data was collected in January/February of 2021, when Ontario just issued the ‘stay at home’ order after COVID cases peaked following Christmas the year before. Experiment 2 data was collected in January/February of 2022 following the Omicron wave, and Western University did not allow first year students (i.e., all my participants) to return to campus or residence until February 28th (after my data collection). It can be expected that participants of both studies were heavily impacted by the pandemic lockdown during their participation in the study, both directly and indirectly. They may be living with family members who were infected, or they themselves may have symptoms. Even in COVID negative participants, the societal and lifestyle disruptions may have severely impacted their mental health and cognitive functioning (Brusaferri et al., 2022; Esposito et al., 2021; Ferrando et al., 2021; Tanaka & Okamoto, 2021; Zhou et al., 2020). Goksu et al. (2021) found that as levels of stress and anxiety increase, levels of motivation and attention to online learning decrease. The tasks used in my studies involved category learning, and it would not be surprising if many participants responded with dwindling motivation and attention to these tasks without reaching their full pre-pandemic potential. Stress has also been shown to drive attention away from the task at hand and towards stress-related subjects (Eysenck et al., 2007; Staal, 2004). Participants may have suffered from intrusive thoughts about the uncertainties of the pandemic, which further diminished their attention to the category learning task. Moreover, during both periods of data collection, my participants oriented their lives around their electronic devices: their school, friends, entertainment were all online. Amidst all these, they completed my study, which of course, was online. Studies have shown that the pandemic led to boredom among students (Chao et al., 2020; Sundström et al., 2019), and boredom has been consistently associated with lower learning outcomes (Banerjee & Rai, 2020; Pekrun et al., 2014; Tze et al., 2016). To possibly make matters worse, participants may have had videos or music playing in the background to counter boredom during their study participation. These are all factors outside of the control of the researchers, and may lead to lower category learning performance.

Furthermore, ratings on the ATQ may also have been impacted by participants' mental state during the pandemic. Despite that the ATQ has been shown to measure traits rather than moment-by-moment changes of emotion, living in the pandemic for months on end may have altered participants’ perception of self compared to pre pandemic times. For instance, negative affect items such as the following: “Sometimes, I feel a sense of panic or terror for no apparent reason”, is expected to elicit an overall high agreeing rating for every participant, irrespective of their baseline temperament. Similarly, temperament trait effortful control concerns the self regulatory ability to focus and shift attention to desired channels. Participants may have noticed that their attention and motivation dwindled after the lockdown due to reasons discussed earlier, and these may be reflected in their self ratings on items relating to effortful control. Along the same lines, it would not be surprising if participants were also experiencing less positive emotionality and gave lower self-rating scores on items relating to extraversion/surgency.

Taken together, the null or inconsistent results across studies may be due to the fact that both the category learning and ATQ measures did not reflect participants' true ability or character. The extraneous variables associated with the pandemic may have interfered with all behavioral and neurophysiological research that were conducted during this time period. Unfortunately, I did not survey participants on their pandemic specific experience, so it leaves only speculation with regards to how reliable the data is. Interested researchers may want to conduct these same studies again to see whether results would differ given a more "normal" social environment.

While the pandemic experience may have undermined the relationship between affective temperament and category learning, there is also the possibility that these traits are not associated with category learning strategy use. I have speculated that in Experiment 1, the specific version of CR task may be too difficult to learn while the specific version of II task may be too easy, there was still a distribution of performance and participants still differed on their default learning strategy. Similarly in Experiment 2, participants differed both on overall performance and optimal strategy learning rate. Given the number of analyses that were run and the number of null results relating to affective temperament, the significant result associating negative affect and lower II performance and the significant effect of extraversion predicting more simple rule use in II task were likely to be false positives.

Potential explanations can also be speculated in the event that these affective temperament effects were real. The association between negative affect and lower overall II performance corresponds to the predictions made by the affect-as-information hypothesis. This theory proposes that higher negative emotions lead to explicit and analytical processing, and this is incongruent with the implicit similarity-based processing required by the II task. Given the general small effects of affective temperament through both of the experiments, these results should be interpreted with caution.

3.4.3. Temperamental Effortful Control and Working Memory

Temperamental effortful control was not a significant predictor of performance in either tasks in Experiment 1, and it was negatively associated with overall performance on both CR and II category learning tasks in Experiment 2. Effortful control was not predictive of default strategy use in Experiment 1 and it inconsistently modulated the effect of affective temperament in Experiment 2. Results were discordant across studies and not aligned with the hypothesis.

Temperamental effortful control relies on executive attention mechanisms (Rothbart et al., 1994; Rueda, 2012). Executive attention is considered to be a component of working memory by Engle and colleagues, this component is defined as the ability to select and maintain task goals and avoid distraction (Engle & Kane, 2004). It is surprising to see that effortful control was associated with lower category learning performance in Experiment 2. Moreover, effortful control also aggravated the negative effect of negative affect on overall II performance, rather than modulating or neutralizing the effect. One explanation for these results is that there was a general reduction of effortful control during the pandemic. McKinney et al. (2020) reported pre-pandemic effortful control ratings in participants of the same demographic as the present studies to range from 1.95 to 6.21. In my sample, this range was 1.84 and 5.84. It can be speculated that the facilitatory effects seen in previous studies may be driven by a whole range executive attention capacity, while the overall lower capacity seen in the present sample may have disguised this relationship. Some COVIS theorists also proposed that executive attention was not required in II type of category learning (Filoteo et al., 2010; Reetzke et al., 2016). However, these do not explain why effortful control was found to have a detrimental effect on category learning. The only logical explanation would be that these effects were false positives.

The reading span task measured both the central executive and storage components of working memory. Interestingly, despite that the executive component of working memory overlaps with the construct of effortful control, Rspan scores did not correlate significantly with temperamental effortful control in any sample of participants. Temperamental effortful control is a concept developed to capture individual differences in emotional regulation, whereas executive attention component of working memory is a concept developed in neurocognitive literature intended to be linked to cognitive control and flexibility. Therefore, despite the conceptual overlap, temperamental effortful control and executive attention component of working memory represents different levels of analysis and may not directly map onto one another (Rueda 2012).

Higher working memory was facilitatory in II learning in Experiment 1 and CR learning in Experiment 2. Previous studies have also reported inconsistencies with regards to the role of working memory in rule-based and similarity-based category learning tasks. Many earlier studies suggested that working memory is critical in learning rule-based tasks (Maddox et al., 2004; Waldron & Gregory Ashby, 2001; Zeithamova & Maddox, 2006). More recent research tends to show that working memory contributes to learning of both types of categories (Craig & Lewandowsky, 2012; Kalish et al., 2017; Lewandowsky et al., 2012). It is baffling that there was no working memory effect in Experiment 1 CR task. It can be speculated that CR performance was more sporadic both because of pandemic stress and this specific version of the task being challenging, thus altered the relationship with working memory in unknown ways. Results differences across studies could also be due to methodological differences (i.e., continuous dimensions vs. discrete dimension). Nevertheless, the significant effect from my studies were consistent with previous findings that working memory is beneficial to category learning.

3.4.4. Conclusions

In conclusion, results from the two studies suggested that temperament traits may not be predictive of people's category learning performance and strategy. Theories of mood states were not predictive of the relationship between affective temperament traits and category learning. Working memory was facilitatory to category learning performance, but its effect did not consistently show up in both tasks across studies. This work sought to use temperament traits and working memory to explain individual differences in category learning strategy use, either because of data quality issues or an actual lack of strong effect, our findings did not provide clear answers. Future research should replicate these studies using post-pandemic data to further clarify the picture.

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4. Chapter 4 - General Discussion

Individuals differ in their strategic approach in classifying their environment. For example, when deciding whether a stranger poses a threat, some people may focus on a stranger's gait whereas others might base their classification decisions on the overall aura they sense from the stranger. The strategy used by the former group is rule-based, people in this group may verbalize the rule as "the stranger is walking neither straight nor with good balance therefore he must be intoxicated and dangerous". The strategy used by the latter group can be described as similarity-based; people in this group cannot describe one or more deterministic features for their classification decision. Instead they evaluated the stranger holistically, and this gestalt reminded them of past experiences or knowledge associated with danger. People's diverse category learning strategies have also been frequently observed in experiments conducted in the laboratory (Johansen & Palmeri, 2002; Little & McDaniel, 2015; McDaniel et al., 2014; Minda & Smith, 2011; Nosofsky et al., 1994; Sewell & Lewandowsky, 2011).

Both in the scoping review and the two empirical studies, I focused my investigation on the types of categorization tasks that were originally developed by proponents of multiple systems models (Ashby et al., 1998; Ashby & Ell, 2001; Ashby & Gott, 1988); specifically, rule-based and similarity-based category learning tasks. The optimal strategy to learn rule-based categories is to find the deterministic dimension(s) and then map the different dimensional values to each category. In the simplest variant, one dimension alone is deterministic of the rule. In more complex variants of the rule-based task, the optimal strategy requires the learner to attend to two or more dimensions conjunctively. For example, if category stimuli are composed of three dimensions each with two values (e.g., size: large or small; color: red or yellow; shape: square or round) and the color and shape are the relevant dimensions. The optimal strategy in this case can be explicitly described as: "stimuli that are both red and round belong to category A, other stimuli belong to category B". In similarity-based categories, the optimal strategy is implicit and the learner needs to integrate two or more stimulus dimensions perceptually at a pre-decisional stage. Rule-based learning requires hypothesis testing of verbalizable rules and effortful working memory engagement, whereas similarity-based learning operates effortlessly and is associated with procedural learning (e.g., (Ashby et al., 1998). Compared to the consensus with regards to the nature of the rule-based learning, there have been debates around whether the similarity-based learning relies on exemplar-based memorization (e.g., Brooks, 1978; Estes, 1986; Medin & Schaffer, 1978; Nosofsky, 1986), prototype abstraction (e.g., Homa et al., 1981; Minda & Smith, 2001; Reed, 1972) or procedural-based cognitive mechanisms (e.g., Ashby & Gott, 1988; Ashby & Lee, 1991; Ashby & Maddox, 1990, 1992, 1993).

Unlike judging whether a stranger poses a danger scenario where both approaches would lead to the same accurate conclusion, rule-based and similarity-based category learning tasks used in experiments are designed to be best-learned by one strategy. Despite the suboptimal performance associated with suboptimal strategies, people again consistently demonstrated qualitatively different learning approaches (Ashby et al., 1998; Donkin et al., 2015; Meeter et al., 2006; Minda & Smith, 2001; Nosofsky & Zaki, 2002; Pelley et al., 2019; Raijmakers et al., 2001; Wills et al., 2015). There are limitations to drawing conclusions about the underlying mechanisms of category learning based on average patterns of performance while overseeing the qualitative differences across individuals (Lee & Webb, 2005; Navarro et al., 2006; Siegler, 1987). Discovering the factors associated with using different strategies and dividing participants based on these should be a critical first step towards studying the underlying learning mechanisms. This dissertation reviews existing evidence and commences the search for new potential predictors (i.e., temperament traits) of strategy preference in category learning.

4.1. Scoping Review

4.1.1. Summary of Results

Through a scoping review, Chapter 2 presented an overview of existing evidence on stable trait differences and category learning strategies. Developmental and aging changes in executive functions was the only factor that produced more-or-less consistent results. Children and older adults tend to show disadvantage in learning both types of categories through difficulty learning complex rules and high distractibility. Despite many studies suggesting these two groups had lower category learning performance, results were inconsistent regarding whether they also used less optimal strategy. Within the cognitive domain, the most frequently studied factor was working memory. While the majority of studies found that working memory was positively related to performance on both types of categories, results concerning strategy use were mixed with some showing a facilitatory effect on optimal strategy use and others showing no relationship. The remaining themes that emerged from this scoping review contained few articles and made it difficult to draw firm conclusions. Therefore, based on this exhaustive examination of existing literature, it remains elusive why healthy adults take qualitatively different approaches to learning categories despite the presence of an optimal strategy.

Another intention of conducting the scoping review was to see whether previous studies have looked at temperament trait effects on category learning. Temperament traits have shown great potential according to my literature search and I was pleasantly surprised to learn that no previous study has made these connections.

4.1.2. Suggested Future Directions

Note that scoping reviews by their nature are not designed to critically appraise existing studies' methodological limitations or potential bias of evidence included. Instead, the purpose of conducting a scoping review is to determine the size and scope of the existing literature on a topic area (Peters et al., 2019). Although the scoping review in this dissertation was not intended to answer a specific question but to survey the existing literature on the topic of "how individual differences in stable traits can impact category learning", the fact that methodological limitations and biases were not evaluated in included studies may still be considered a limitation. Future studies that wish to extend from the present work should consider adding the following details in their synthesis of evidence. First, category learning tasks used by different research groups may have used different strategy modeling methods/code. In addition, across a certain type of category learning tasks, for example: conjunctive rule-based tasks, there may be many variants (e.g., decision-bound task, Shepard Hovland & Jenkins (1961) task, etc). It may be of interest to compare ways of strategy modeling within one variant of task or across different variants of tasks and evaluate whether certain biases were embedded in certain methodologies. Second, different studies may evaluate strategy effects on category learning differently. It may be important to assess how individual studies relate stable traits with strategy, and how these methodological differences might map onto one another.

In the next section, I interpret results from the two empirical studies in this dissertation and discuss implications.

4.2. Affective Temperament

4.2.1. Neurobiological Basis of Affective Temperament Traits

Temperament is composed of emotional reactivity and emotional regulation (Rothbart & Bates, 2007). Affective temperament traits extraversion/surgency and negative affect falls into the component of emotional reactivity. Studies have uncovered structural and functional correlates of affective temperament traits and compared these with affective states. Accumulating evidence has been suggesting that individuals with certain affective temperament traits tend to show higher resting state activities in relevant brain regions in much the same way as during elicited transient affect (see Whittle et al., 2006 for a review). For example, increased amygdala activation can be observed during negative affective states. Davidson and Henriques (2000) found that the amygdala activation at rest can be used to predict the severity of trait negative affect. Patients with high negative affect related disorders such as anxiety disorders have particularly high resting state amygdala activation (Drevets, 1999). Other studies have also shown that reduced activity in right dorsolateral prefrontal cortex is linked to both negative affective states in healthy individuals and in patients with mood disorders with chronic negative affect as a feature (Drevets, 1999; Liotti et al., 2000; Mayberg, 2003; Mayberg et al., 1999). Further studies found higher activity in the ventral anterior cingulate cortex has been associated with induced negative mood in healthy adults as well as individuals who self-reported high trait negative affect (Liotti et al., 2000; Zald et al., 2002). Comparably less literature has drawn neurophysiological connections between positive affective states and trait positive affectivity (i.e., extraversion/surgency) compared to that of negative affect, nonetheless available evidence does point to the existence of a relationship. Functional studies have shown that increased dorsal anterior cingulate cortex activity is linked to positive affective states, whereas decreased activity in this area has been reported in patients with mood disorders or schizophrenia characterized by anhedonia (Allman et al., 2001; Sigmundsson et al., 2001). Moreover, activity in the left dorsolateral prefrontal cortex has been observed both in healthy adults experiencing positive emotional states and trait extraversion (Davidson et al., 2002; Harmon-Jones & Allen, 1997). The above evidence established firm grounds to draw connections between affective traits and states. Based on these connections, we can then infer that research on affective states is relevant in making predictions for the effects of affective temperament traits on cognition.

4.2.2. Theories of Affective States

Dopaminergic Theory

Two theories of affective states were referred to in this dissertation: dopaminergic theory and the affect-as-information hypothesis. Both theories make predictions of the ways in which affective states may impact cognitive processing and distinguish the effects led by positive or negative affect. Dopaminergic theory originated from cognitive psychology as a category learning specific theory, it proposes an overall facilitatory effect of positive mood on both rule-based and similarity-based category learning (Ashby et al., 1999, 2002). This theory argues that the effects of positive affect on cognition are mediated by dopamine. It also assumes that increase of dopamine release in the anterior cingulate cortex and prefrontal cortex during transient positive mood states increases cognitive flexibility and verbal fluency. Ashby and colleagues suggest that positive affect facilitates explicit rule-based learning and implicit similarity-based learning. Cognitive flexibility and verbal fluency are related to rule selection and rule switching (Owen et al., 1993), thus improving the efficiency of discovering the optimal strategy. The dopaminergic theory further postulates that striatal dopamine is critical in mediating feedback in procedural learning (Ashby et al., 2007). Positive affect facilitates similarity-based tasks through projecting dopamine into the striatum, a critical region involved in this type of processing. Moreover, cognitive flexibility may also speed up the process of exhausting potential rule-based strategy before resorting to the similarity-based strategy. Empirical evidence has supported the dopaminergic theory on its assumption that positive mood facilitates rule-based category learning, but results were less consistent with regard to similarity-based category learning (Nadler et al., 2010; Nielsen & Minda, 2018).

Affect-as-Information Framework

The affect-as-information framework was developed in the realm of social psychology, it contends that specific information-gathering mechanisms are associated with certain emotional valence (Clark & Isen, 1982; Clore, 1992; Gasper & Clore, 2000; Schwarz & Clore, 1983). Specifically, people are more motivated to seek external information and be analytical when they are in negative affective states than in positive affective states, whereas positive affective states tend to be associated with implicit processing of internal information and low motivation to seek explicit explanations. Relevant studies have shown that negative affect, such as anxiety and stress can trigger an effortful, analytical processing style (Clark & Isen, 1982; Isen, 1987; Park & Banaji, 2000; Schwarz & Bless, 1991). Studies on positive mood and cognition are also abundant and findings indicate that people in a good mood tend to reach decisions more quickly, use less information, and avoid analytical thinking (Ashby et al., 1999; Bless et al., 2006; Fiedler, 2001; Fredrickson, 2009; Hertel & Fiedler, 1994; Isen & Daubman, 1984). These results are consistent with the claims made by the affect-as-information framework. Despite this being a social psychology theory that is often used to evaluate heuristic and bias within the social theme, the cognitive relevance is strong enough to draw a connection to pure cognitive tasks such as category learning. When this framework is applied to the category learning context, it would hypothesize that positive mood should aid similarity-based category learning due to the congruency between mood-elicited implicit processing and the optimal strategy, whereas negative affective states should facilitate rule-based category learning because of the congruency between mood-elicited analytical processing and task-appropriate strategy.

4.2.3. Effects of Affective Temperament Traits in the Studies of Chapter 3

In Chapter 3, I conducted two empirical studies to examine whether temperament traits can be predictive of individual differences in learning rule-based (i.e., CR) and similarity-based (ie., II) category learning tasks. Specifically, whether certain temperament traits are linked to an advantage in acquiring the optimal strategy on a specific type of category. Hypotheses were made based on both the dopaminergic theory and the affect-as-information framework to see which theory makes more accurate predictions. Dopaminergic theory proposes that higher extraversion should be related to an advantage in learning both types of tasks, whereas high negative affect should not have a different effect than neutral mood. Affect-as-information framework postulates that higher extraversion should only lead to an advantage in learning similarity-based tasks, while higher negative affect should be related to an advantage in learning rule-based tasks.

Summary of Results

I did not find any affective temperament effect in Experiment 1, but negative affect showed a significantly detrimental effect in Experiment 2 II task. Taken alone, this effect seems to support the hypothesis made by the affect-as-information framework since the narrow processing scope associated with negative affect is incongruent with the optimal holistic learning mode of II task. However, I failed to observe the same effect in Experiment 1 II task and there was no facilitatory effect of extraversion seen in either of the II tasks. Contrarily, extraversion was seen to have an negative effect on II performance in Experiment 2. Moreover, the effect of affective temperament was not observed in predicting strategy learning in either type of categorization tasks across the experiments. Therefore, the overall picture of the results suggest small to no effect of affective temperament traits on category learning, and the lone significant effect of negative affect may have been a false positive.

Interpretations of Results

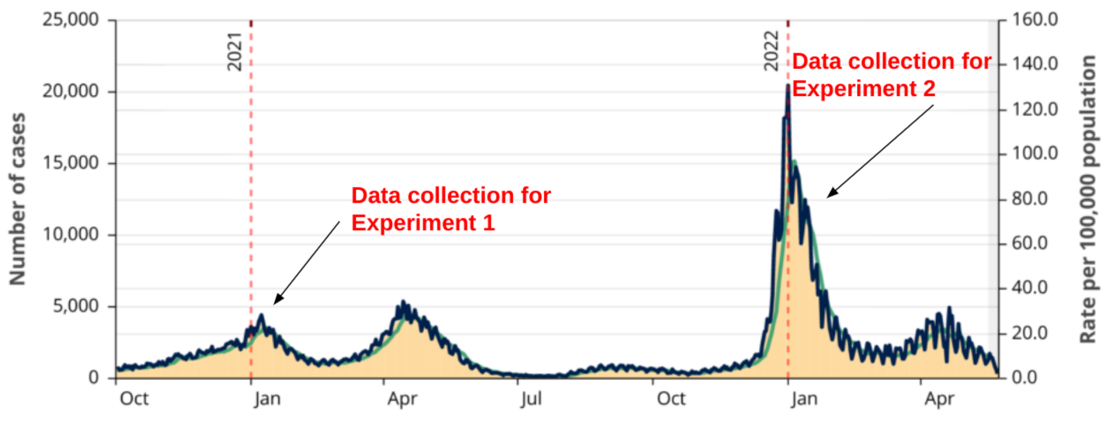
Despite that results did not support either theory of affective states and suggested an overall lack of relationship between affective temperament traits and category learning, my studies were still the first ones to test out these interesting hypotheses. Several interpretations for the lack of affective temperament effect can be speculated. First, temperament constructs were developed in social and personality psychology with socioemotional underpinnings and may have stronger predictive power on emotional stimuli or stimuli with interpersonal implications. The category learning stimuli used in my experiments were emotionally neutral. These may not have activated the approach-avoidance mechanism associated with affective temperament traits (Rothbart et al., 2000; Wiltink et al., 2006) to really differentiate participants on their affective experiences. Previous studies that drew functional and structural connections between affective states and traits tend to examine affective traits in patients with mood disorders rather than healthy participants (Drevets, 1999; Liotti et al., 2000; Mayberg, 2003; Mayberg et al., 1999). It is possible that the expressions of affective traits in the brain are different in healthy individuals, maybe the resting level activities do not differ in the emotional processing centers for healthy people irrespective of their self-ratings on the affective temperament scales.

Second, the overall average performance for CR and II category learning tasks across the tasks was around 75%, and the Experiment 2 II task only had overall performance of 63%. Past studies suggest that using a suboptimal strategy can yield maximum performance of about 75% and adoption of the optimal strategy is the only way to surpass this performance threshold. One may speculate that a large proportion of participants in my studies may have used suboptimal strategies throughout the tasks to achieve a "good enough" performance and failed to ever discover the optimal strategy. The underlying assumption behind performance analysis was that more consistent use of the optimal strategy should be associated with better performance, so if a trait is linked to higher performance then it is linked to an advantage in using the optimal strategy. When the performance is low across most participants, a relatively high performance may not necessarily be associated with using the optimal strategy. For instance, low overall performance may mean that a large group of participants were using suboptimal strategies. Among the suboptimal strategies, one may lead to superior performance compared to the rest, and moderately high performance may be linked to usage of this superior suboptimal strategy. In this case, the analyses of performance become less relevant and so are the hypotheses relating to temperament traits in these analyses. It can be speculated that the small learning effect may be the reason behind the null results seen in my study, and reasons behind low learning may be due to various circumstantial factors I discuss next.

Third, as discussed earlier, there was a potential impact of the COVID-19 pandemic on data quality. See **Figure 4.1** for the approximate time period when Experiment 1 and Experiment 2 data was collected. Data collection for both experiments took place in the midst of a particularly severe wave of the pandemic. It can be expected that overwhelming anxiety accompanied by social isolation impacted participants' learning on category learning tasks as well as self-ratings on the ATQ. Moreover, participants may also experience pandemic related stress such as living with an infected person in the same household or being fed up by their roommates but have no option of moving. They may also have suffered from intrusive thoughts about the uncertainties of the pandemic. Stress has been shown to drive attention away from the task at hand and towards stress-related subjects (Eysenck et al., 2007; Staal, 2004). Furthermore, it would not be surprising that these young undergraduates were bored and experience a dulled affect from having to revolve around their computer for all activities and not placing great importance on the online study they signed up for, they may have engaged in multitasking while completing the study. These circumstantial factors may have either worked alone or jointly to contribute to low data quality, which in turn may have led to the null results seen in my studies. There is the possibility that temperament trait effects do exist, but it is impossible to decipher without knowing the quality of the data at hand.

Figure 4.1: *COVID-19 daily case counts and rate by reported date in Ontario with arrows pointing at approximate data collection times for studies in Chapter 3*

October 1, 2020 to May 23, 2022



Note. The yellow filled area shows the case counts by reported data. The arrows point at the approximate time period when Experiment 1 and Experiment 2 data was collected.

4.3. Temperamental Effortful Control

4.3.1. Neurobiological Basis of Temperamental Effortful Control

It has been argued that temperamental effortful control shares the same underlying mechanisms as executive attention (Posner et al., 2007; Posner & Rothbart, 2007). Similarly to linking affective states and traits, studies have also uncovered structural and functional correlates of trait effortful control and compared these with temporary engagements of executive attention and regulation through cognitive tasks. Dorsal anterior cingulate cortex is thought to be associated with executive attention or response regulation. Activation of the dorsal anterior cingulate cortex has been observed among healthy adults while performing cognitive tasks involving executive attention and control, such as the Stroop interference task (Drevets & Raichle, 1998), and the go/no-go task (Casey et al., 1997). Low activity in the dorsal anterior cingulate cortex has been reported in patients with disorders of chronic inattention and impulsivity such as the attention-deficit/hyperactivity disorder (Bush et al., 1999) and substance abuse disorder (Forman et al., 2004; Kaufman et al., 2003). Dorsolateral prefrontal cortex also plays a significant role in the neutral network subserving executive attention and control. Temperamental effortful control continues to develop throughout the childhood which can be attributed to the brain's development of the executive attention system. One study administered the Stroop interference task to a sample with age ranging from 7 to 29 years old. It showed that dorsolateral prefrontal cortex activation increased with age and so is the behavioral performance (Schroeter et al., 2004). Similar findings were also shown within the category learning research. Behavioral performance on rule-based tasks (i.e., engages executive attention) tend to be higher in older children or young adults compared to younger children (Davidson et al., 1999; Davidson & Henriques, 2000; Drevets, 1999; Schaefer et al., 2002; Zald, 2003).

The above evidence clearly laid out the connections between trait effortful control and momentary engagement of executive attention. We have reasons to believe that people's self-ratings on the temperamental effortful control scale would reflect their levels of executive attention that would be engaged in the category learning tasks.

4.3.2. Effects of Temperamental Effortful Control in the Studies of Chapter 3

Executive attention is thought to be beneficial in both rule-based and similarity-based category learning tasks. A rule-based category is best learned through explicit hypothesis-testing, which requires heavy involvement of executive attention (Ashby et al., 1998, 1999). Specifically, the participant needs to attend to a certain feature of the stimuli to test its validity as the optimal rule, at the same time not getting distracted by irrelevant features. If the tested rule was incorrect, the participant needs to shift attention to a new feature and conduct hypothesis-testing again. The optimal approach to learn the similarity-based category is through implicit holistic processing. It has been suggested that higher executive attention is facilitative in this type of learning as well (Ashby et al., 1998). Specifically, the default approach people tend to use is one that is rule-based, therefore, higher executive attention facilitates the exhaustion of potential rules so the learner can swiftly switch to an implicit approach. Temperamental effortful control has also been shown to modulate the effects of emotional reactivity. Individuals with higher negative affect are less likely to display problems when they have high effortful control (Drevets & Raichle, 1998; Rothbart & Bates, 2007; Rothbart & Posner, 2006). Therefore, in the two experiments of Chapter 3, I looked at the main effect of temperamental effortful control as well as the interaction between each affective temperament trait and effortful control.

Summary of Results

Contrary to the hypothesis, I did not observe a facilitatory effect of temperamental effortful control across the two experiments. In Experiment 1, effortful control was not predictive of either CR or II overall category learning performance or strategy in the first block. In Experiment 2, effortful control was negatively contributing to both CR and II overall task performance, as well as slowing down the strategy learning rate on the II task. Modulating effect of effortful control was seen in Experiment 2 TTC analysis of the CR task and Experiment 2 performance analysis of the II task. In the former case, higher effortful control seems to have reversed the slowing down effect of extraversion on learning the optimal CR strategy but this effect was marginal. In the latter case, effortful control further contributed to the lower performance on the II task led by negative affect. Due to the inconsistent results and sporadic occurrence of significant effect, it can be speculated that the modulating effect of temperamental effortful control on affective temperament may not truly have an association with either type of category learning.

Interpretations of Results

Although the results described in Chapter 3 did not support previous findings that showed facilitatory effects of executive attention, my studies were still the first to test the trait effect of executive attention. Several interpretations can be speculated for the results relating to temperament effortful control. First, there may have been a general reduction of effortful control during the pandemic. McKinney et al. (2020) reported pre-pandemic effortful control ratings in participants of the same demographic as the present studies to range from 1.95 to 6.21. In my sample, this range was 1.84 and 5.84. It can be speculated that the effects seen in previous studies may be driven by a whole range of executive attention capacity. It is possible that a larger proportion of individuals who participated in pre-pandemic studies had higher perceived levels of executive attention, and these people may play a critical role in driving the facilitatory effects of executive attention on cognitive tasks. It may also be true that this facilitatory effect does not exist among individuals with low or moderate levels of executive attention. Therefore, it can be speculated that the overall lower effortful control ratings seen in the present sample may have disguised the relationship. However, while null results seen in Experiment 1 can still be explained, the counterintuitive reversed relationship seen in Experiment 2 across both category learning tasks was indeed baffling.

Second, as speculated for the lack of affective temperament effects in the previous section, a large proportion of participants in my studies may have used suboptimal strategies throughout the tasks to achieve a “good enough” performance and failed to ever discover the optimal strategy. When the performance is low across most participants, a relatively high performance may not necessarily be associated with using the optimal strategy. In this case, the analyses of performance become less relevant and so are the hypotheses relating to temperament traits in these analyses. It may be possible that participants who used similarity-based strategy for a significant period of time on the CR task had higher overall performance compared to participants who used single-dimensional rule consistently. One can argue that executive attention is linked to analytical processing and attention focusing, and using a single-dimensional rule requires these cognitive properties. In this scenario, higher executive control may have been associated with lower performance. Following from the observation that effortful control scores tend to be lower than pre-pandemic times, it is reasonable to think that the individuals with moderately high effortful control only had the capacity to find and apply a simple rule but did not have the level of executive attention required to discover the optimal strategy. These are pure speculations for the counterintuitive results we saw in Experiment 2. However, it would be interesting to further examine whether there would be a consistent negative relationship between executive attention and category learning performance among individuals with low to moderate levels of executive attention.

Third, research linking trait executive attention and momentary engagement of executive attention tend to examine this trait in highly disordered populations (Bush et al., 1999; Forman et al., 2004; Kaufman et al., 2003). It is possible that the expressions of temperamental effortful control in the brain are different in healthy individuals compared to disordered populations, maybe the resting level activities do not differ in the brain's inhibitory control centers for healthy people irrespective of their self-ratings on the effortful control scale. Fourth, as discussed in the affective temperament section, the COVID-19 pandemic may have significantly impacted the data quality by reducing motivation and the desire to respond.

4.4. Working Memory

Working memory has been the most well studied predictor of individual differences in category learning (Craig & Lewandowsky, 2012; Decaro et al., 2008; DeCaro et al., 2009; Kalish et al., 2017; Little & McDaniel, 2015; McDaniel et al., 2014). Results tend to suggest a positive relationship between working memory and learning on both rule-based and similarity-based categorization tasks (Craig & Lewandowsky, 2012; Lewandowsky, 2011; Lewandowsky et al., 2012), although there are few studies suggesting a lack of relationship (Goldwater et al., 2018; Iwashita, 2020). In the two empirical studies of Chapter 3, working memory was measured as a covariate through a reading span task. Working memory has been suggested to encompass two components, executive attention and storage (Baddeley, 1986). In my studies, it can be thought that executive attention was measured both through self-ratings on the temperamental effortful control scale of the ATQ and partially by the reading span task. Interestingly, reading span scores did not correlate with effortful control scores in any of the participant samples, despite the partial conceptual overlap. This may suggest that despite the conceptual overlap, temperamental effortful control and working memory are separate constructs and may not easily map onto one another. It was hypothesized that, same as for temperamental effortful control, working memory should also have an overall facilitatory effect on both types of category learning.

Summary of Results

Working memory had a facilitatory effect on overall II performance in Experiment 1 and overall CR performance in Experiment 2. Working memory was not predictive of strategy-related measures (i.e., first block strategy in Experiment 1; TTC in Experiment 2).

Interpretations of Results

It is interesting that there was no working memory effect on the CR task in Experiment 1 or II task in Experiment 2. Note that the CR task in Experiment 1 was considered very difficult (M = 73%) and II task in Experiment 2 also had a low overall performance (M = 63%). It is possible that a large proportion of participants struggled with these tasks regardless of their working memory, thus no relationship can be discovered. Earlier research from proponents of COVIS suggested that higher working memory does not facilitate similarity-based category learning as much as rule-based category learning (Ashby et al., 1998; Decaro et al., 2008; DeCaro et al., 2009; Markman et al., 2006; Waldron & Ashby, 2001). However, other studies have shown that higher working memory is the universal benchmark for optimal performance across all tasks (Kalish et al., 2017; Lewandowsky, 2011; Newell et al., 2011; Neys & De Neys, 2006; Stanovich & West, 2000). These differences may be due to variations in experimental design, but also demonstrated the inconsistencies around the working memory effect. Another potential reason for the lack of working memory effect may be that undergraduate participants were more or less homogeneous in cognitive capacities when subjected to a span task (standard error for Rspan score in any participant sample ranged from 0.066 to 0.095). Therefore, this may have restricted the variances of the data and reduced the magnitude of correlation. Furthermore, as previously discussed, the pandemic may have impacted data quality and potentially buried certain effects of the predictors on dependent variables.

4.5. Conclusion

This dissertation took the first step in the uncharted research territory to explain variability in category learning behaviour through temperament trait differences. In Chapter 2, I reviewed extant literature that used stable individual differences traits to explain differences in category learning performance and strategy use. Most of the studies focused on developmental effects and effects of working memory, however, no single trait consistently predicted either categorization performance or strategy use. In addition, the scoping review showed no prior study had examined temperament traits' effect on categorization. In Chapter 3, I conducted two empirical studies and results suggested a lack of temperament trait effects on either CR or II category learning. The effect of working memory was not consistently found across all category learning tasks across the 2 experiments, but existing effects suggested a positive relationship. My work represents a significant first step in examining temperament traits as predictors of people’s category learning performance and strategy.

It is worth noting that one common constraint subjected to all behavioral data collected online during the pandemic is the lack of control with regards to data quality. Researchers have no way of knowing how much emotional distress, anxiety, and/or boredom affected task performance. To make matters worse, my studies invited participants to self-report their affective traits during this stressful time. It is unclear how much of these ratings are influenced by participants' current state of mind, and by current, I mean during the two-year period of on-and-off lockdowns. These two years may have very well altered participants' self-perception of traits, even if the traits themselves are stable. For example, before the pandemic, I generally spent my free time reading or hitting the gym which are both indoor activities, but since the pandemic I have been spending much more time outdoors to engage in activities such as fishing and hiking (to look for new fishing spots). It is reasonable to think that lifestyle changes may lead to changes in self-perception of stable traits. Extraverted participants may perceive themselves as less extraverted due to the inability to socialize in the past two years. Therefore, readers may want to take the results of the present dissertation with a grain of salt since there may be a temperament effect that has been buried due to unknown data quality. Future studies should replicate the empirical studies in this dissertation to further understand the robustness of the observed findings.

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Appendix A

Chapter 2: Individual Differences and Category Learning Performance and Strategy - A scoping review protocol

Abstract

Background: Categorization is a fundamental phenomenon of cognition and intelligent behavior. Previous studies have shown that individuals may differ in their strategic approach in learning to categorize (Donkin et al., 2015; Minda & Smith, 2001; Pelley et al., 2019). For example, a subgroup of participants may show a strong tendency or preference for rule use (e.g., red objects belong to category A, green objects belong to category B) and apply this strategy to a similarity-based category (e.g., objects that look similar belong together) despite having lower performance accuracy than people who used the task appropriate strategy. Understanding the individual differences factors that are associated with suboptimal category learning is the first step towards identifying ways to promote optimal performance and effective knowledge transfer.

Objectives: This scoping review aims to examine past evidence on the question: What individual differences factors are associated with differential performance and strategy use in learning rule-based or similarity-based categories, and in what way?

Methods: We developed a scoping review protocol following the guidelines for conducting scoping review by the Joanna Briggs Institute (Peters et al., 2019). Four database (PsycINFO ProQuest, PubMed, Web of science, Scopus) and two grey literature database (Dissertation and Thesis ProQuest and PsyArXiv preprints) were searched, and the search were limited to English articles from 2000 and 2021 that used experimental or quasi-experimental design. Articles will be included if their primary aim is to examine one or more sources of stable individual differences and their relationship with category learning performance and/or strategy use. Studies that examine clinical or cognitively impaired populations will not be included in this review.

Results: The sources of individual differences will be grouped into themes (e.g., age, working memory capacity, culture) determined post-hoc based on the selected papers. Frequency counts of the number of studies assessing each individual difference factor will be calculated and mapped. Study results will be qualitatively summarized and discussed with a focus on each factor's effects on category learning strategy use and performance. Research gaps will be identified and discussed.

Conclusions: This study will bring together existing literature that examines individual differences in category learning performance and strategy use, and allow the readers to compare the ways in which the same or different sources of individual difference may impact category learning. Results from this study should help with identifying gaps in research for future exploration.

Introduction

Rationale

The rationale for conducting this review is to discover what stable individual differences factors have been explored in previous research in the past 20 years that are associated with category learning performance and strategy use variations.

Objective

The aim of this review is to provide an overview of studies assessing the effects of various stable individual differences factors in learning rule-based or similarity-based categories. A scoping review is the suitable approach because this evidence synthesis process allows us to rapidly gather a broad range of data sources as outlined in the Joanna Briggs Institute (JBI) scoping review manual (Peters et al., 2020). The review will be formatted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews (PRISMA-ScR).

Methods

Eligibility Criteria

We will include studies using experimental or quasi-experimental designs to compare category learning performance and strategy use among groups that differ on some aspect of stable traits. The age of participants in the studies will range from young children to older adults. Age-appropriate cognitive development and cognitive status is required, clinical populations and individuals with impaired cognitive functions are not included. An eligible study should use one or more categorization task(s) that can be learned through a rule-based or a similarity-based strategy, or both. The categorization task can be in any modality, such as visual, auditory or speech; feedback to categorization response can be present or absent. Eligible studies should be written entirely in English, and are made available between 2000 and 2021. We will not include any studies that create differences between groups through experimental manipulation, only studies that investigated intrinsic stable trait differences will be included. See Appendix A for inclusion/exclusion criteria in table format.

Information Sources

The search sources are PsycInfo (ProQuest), PubMed, Web of science, Scopus, Dissertation and Thesis (ProQuest) and PsyArXiv preprints. All listed databases were first searched on April 22nd 2021. A secondary search across all databases was conducted on May 13th 2021 because new keywords were identified.

Search Strategy

A comprehensive first search strategy was developed based on the number of results returned from the primary database -- PsycINFO (ProQuest). This is to ensure that the evidence yielded is neither too narrow nor too broad.

The first search strategy for PsycINFO (ProQuest) was:

ti(categorization OR category learning) AND noft(rule OR abstraction OR explicit OR implicit OR procedural OR memorization OR global OR local OR broad OR narrow OR strategy OR analytic OR heuristic OR intuitive) NOT noft(animal OR medical OR computer OR words OR faces OR intervention OR social OR semantic OR social OR linguistic OR gender OR management OR public OR physiology)

The secondary search strategy with additional keywords for PsycINFO(ProQuest) was:

ti(categorization OR category learning) AND noft(culture OR preference OR individual differences) AND noft(rule OR abstraction OR explicit OR implicit OR procedural OR memorization OR global OR local OR broad OR narrow OR strategy OR analytic OR heuristic OR intuitive) NOT noft(animal OR medical OR computer OR words OR faces OR intervention OR social OR semantic OR social OR linguistic OR gender OR management OR public OR physiology)

The search strategies were also applied to the other 3 databases. Gray literature databases (i.e., ProQuest Dissertation and Thesis Global, Psyarxiv) were also searched using the same keywords and potential relevant articles were manually selected. Further searches will be conducted following the discovery of additional keywords during screening.

Reference lists of the included papers after full-text review will be searched for additional articles based on title relevance, articles that cited the included papers will also be examined. This interactive process will continue for each newly added paper. Papers that are added at this stage will be directly imported to the full-text screening step.

Data Charting Process

Study screening will be conducted using Covidence software. Titles and abstracts will be screened based on pre-specified inclusion and exclusion criteria. Two reviewers will independently judge the relevance of the articles, and the disagreement will be resolved by a third reviewer. Before the screening process, the reviewers will pilot the selection criteria on 10 randomly sampled articles and discuss their rationales for inclusion or exclusion. This step should resolve any potential discrepancies in interpreting the scope of the review.

Full-text review will first be done side-by-side with data charting by one reviewer. Extracted data from the selected studies will be summarized in a chart. The chart columns will be developed by

2 reviewers during the piloting stage of full-text screening, through charting 10 randomly sampled articles. The first reviewer will read the articles in full and extract the ones that she/he votes to include. She/he will also look for relevant studies in the reference lists of included studies and relevant studies that have cited the included studies. After the first reviewer finishes charting all studies, the second reviewer will then begin full-text screening votes on Covidence. For any inclusion votes, the second reviewer will look for data charting records from the first reviewer and review the content of the chart. If disagreement on whether or not to include a paper occurs, the two reviewers will discuss their rationales until the conflict is resolved.

Data Items:

Paper citation,

Year of publication,

Country of data collection,

Aims/objectives,

Population,

Sample size,

Age group,

Specific source of individual differences,

Tasks used to measure individual differences,

Baseline tasks to ensure no other differences exist between groups,

Types of categorization task used (task procedure and category characteristic),

Modality of the categories (e.g., visual, auditory),

Key results (how individual differences affect category learning performance and strategy use).

Additional data relevant to the research question may be determined post-hoc and included as charting will be an iterative process. Data charting will be conducted by one reviewer and verified by a second reviewer.

Critical Appraisal of Individual Sources of Evidence

We do not plan on conducting a critical appraisal of the sources of evidence included in this scoping review. Due to the relatively broad scope of this review, a large variety of experimental design and research methodologies may be included. Therefore, the current priority is to identify gaps in the literature which will pave the way for more systematic approaches.

Results

Selection of Sources of Evidence

We will prepare a flow diagram following the PRISMA-ScR checklist guidelines (Tricco et al., 2018; see Appendix B for the checklist) to report the number of studies screened, the number of studies included at each stage, reasons for exclusion at the full-text screening stage, and total number of studies included at the end.

Characteristics of Sources of Evidence and Results of Individual Sources of Evidence

These information will be included in the data chart if deemed to be relevant to the review objectives.

Synthesis of Results

The data extracted from the “Data Charting Process” phase and frequency counts from the “Synthesis of Results” phase will be presented in tables. The sources of individual differences will be grouped into themes (e.g., age, working memory capacity, culture) determined post-hoc based on the selected papers. Frequency counts of the number of studies assessing each individual difference factor will be calculated and mapped. Study results will be qualitatively summarized and discussed with a focus on each factor’s effects on category learning strategy use and performance. Research gaps will be identified and discussed.

Discussion

Presentation of the Results (Summary of Evidence, Limitations, Conclusions)

Qualitative summaries and discussion of the study results in relation to the scoping review objective will be organized by sources of individual differences. Limitations of the review process, implications and conclusions will also be provided.

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Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Annals of Internal Medicine*, *169*(7), 467–473.

Appendix B

Chapter 3: Ethics Approval

Western Research

Date: 2 September 2021

To: Dr. John Paul Minda

Project ID: 116787

Study Title: Temperament Trait and Perceptual Category Learning Strategy Preference

Application Type: NMREB Amendment Form

Review Type: Delegated

Full Board Reporting Date: 01/Oct/2021

Date Approval Issued: 02/Sep/2021 21:41

REB Approval Expiry Date: 18/Dec/2021

Dear Dr. John Paul Minda,

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the amendment, as of the date noted above.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
new_visual_stimuli_house	Other Data Collection Instruments	19/Jul/2021	1
SONA_online_recruitment	Recruitment Materials	30/Aug/2021	1
poster_recruitment	Recruitment Materials	30/Aug/2021	1
SONA_inperson_recruitment	Recruitment Materials	30/Aug/2021	1
amendment_2 LOIC_Aug 30	Written Consent/Assent	30/Aug/2021	3
clean_implied_LOIC	Implied Consent/Assent	30/Aug/2021	3

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Ms. Katelyn Harris , Research Ethics Officer on behalf of Dr. Randal Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Appendix C

Chapter 3: Reading Span Sentences

Meaningfulness (Y/N)	Sentence	Number of Words	Final Word	Syllable	Number of Letters
Y	"Clowns are funny",	3	funny	2	5
Y	"The floor is green",	4	green	1	5
Y	"She replies the call",	4	call	1	4
N	"He cooked an impressive past",	5	past	1	4
N	"Pink horses are dancing samba",	5	samba	2	5
Y	"The song evoked memories with them",	6	them	1	4
Y	"Many people pollute the air",	5	air	1	3
Y	"He told her the happy news",	6	news	1	4
Y	"His shoes have a red shine",	6	shine	1	5
N	"The shoe laughed at the tree",	6	tree	1	4
N	"Flowers enjoy bathing in traffic jams",	6	jams	1	4
N	"Air visits its doctor weekly",	5	weekly	2	6
N	"The worm cooked a great meal",	6	meal	1	4
Y	"Hotels need guests to make profit",	6	profit	2	6
N	"Snow likes reading the yellow press",	6	press	1	5
N	"Blood is good in chess",	5	chess	1	5
N	"He is drinking a forest",	5	forest	2	6
Y	"There is beer in the fridge",	6	fridge	1	6
Y	"She is an a bad mood",	6	mood	1	4
N	"The brush speaks a poem",	5	poem	1	4
Y	"She gave him a gift",	5	gift	1	4
Y	"Her car is black",	4	black	1	5
N	"You are too late without grass",	6	grass	1	5
N	"They escaped in an ant",	5	ant	1	3
N	"The income debates because of sun",	6	sun	1	3
Y	"He is involved in charity work",	6	work	1	4
Y	"She knows many witty people",	5	people	2	6
Y	"We had a huge party",	5	party	2	5
Y	"Promises are an awkward thing",	5	thing	1	5

N	"Glass composes jam",	3	jam	1	3
Y	"Sometimes no words are needed",	5	needed	2	6
N	"Tea was to happy to drink",	6	drink	1	5
N	"The pen attempted a three-point shot",	6	shot	1	4
N	"Hope swallowed the ring",	4	ring	1	4
Y	"Chairs can be red",	4	red	1	3
N	"Watches create honey",	3	honey	2	5
Y	"She has a nice voice",	5	voice	1	5
N	"The plain dreamed of his birth",	6	birth	1	5
N	"The door whispered to a child",	6	child	1	5
N	"Fish cut their nails after lunch",	6	lunch	1	5
Y	"He felt bad after his test",	6	test	1	4
N	"Rain relaxed at a hotel",	5	hotel	2	5
Y	"Blue is her favourite colour",	5	colour	2	6
Y	"Their silly behaviour was received badly",	6	badly	2	5
Y	"Some people are afraid of flying",	6	flying	2	6
N	"Moonlight broke his right head",	5	head	1	4
N	"The foot sang a song",	5	song	1	4
N	"Shirts organize a sea",	4	sea	1	3
N	"Birds like to play tennis",	5	tennis	2	6
N	"He phoned some mountains before sunset",	6	sunset	2	6
N	"Couches like playing cards at night",	6	night	1	5
N	"Bears fly over sea level",	5	level	2	5
N	"Freeze performed a piano play",	5	play	1	4
Y	"Both of them missed the flight",	6	flight	1	6
N	"Ice warmed her nose",	4	nose	1	4
N	"The trains always delay in hell",	6	hell	1	4
Y	"She likes his good looks",	5	looks	1	4
N	"Pillows usually sleep long",	4	long	1	4
N	"He cut himself with a ball",	6	ball	1	4
Y	"Daily showers should be the rule",	6	rule	1	4

Appendix D

Chapter 3: Demographic Questions

1) Is English your first language? (Yes/No)
    a) What is your first language?
2) What is your race/ethnicity?
    i) Asian or Pacific Islander
    ii) South Asian
    iii) Black or African American
    iv) Hispanic or Latino
    v) Native American or Alaskan Native
    vi) White or Caucasion
    vii) Multiracial or Biracial
    viii) Not listed here
3) What is your age?
4) To which gender identity do you most identify with?
    i) Male
    ii) Female
    iii) Trans male/Trans man
    iv) Trans female/Trans woman
    v) Genderqueer/Gender non-conforming
    vi) Different identity (specify below)
5) What sex were you assigned at birth, meaning on your original birth certificate?
    i) Male
    ii) Female
6) Highest degree completed
    i) Below high school
    ii) High school
    iii) Bachelor's degree
    iv) Maters' degree
    v) Doctorate degree

vi) College/Vocational training

7) Country of origin
8) Country of residence
9) Have you been diagnosed with any disability or impairment? (Yes/No/I prefer not to answer)
   a) If yes, which of the following have you been diagnosed with? (Mark all that apply)
      i) A sensory impairment (vision or hearing)
      ii) A mobility impairment
      iii) A learning disability (e.g., ADHD, dyslexia)
      iv) A mental health disorder
      v) A disability or impairment not listed above

Curriculum Vitae

Name	Tianshu Zhu (Toka)
Education	*Ph.D. Cognitive Psychology (Expected)* The University of Western Ontario; London, ON; 2022 *M.Sc Cognitive Psychology* The University of Western Ontario; London, ON; 2018 *B.A. Honours Specialization in Psychology* *Minor: German Language and Culture* The University of Western Ontario; London, ON; 2015
Honours and Awards	*Mitacs Globalink Research Scholarship* - 2019 *Western Entrance Scholarship* - 2010 *Alexander Rutherford Scholarship* - 2010
Related Work Experience	*Undergraduate Course Instructor* The University of Western Ontario; 2022 *Mitacs Globalink Research Internship* University of New South Wales; Sydney, NSW, Australia; 2019 *Research Assistant* The University of Western Ontario; 2015-2016
Related Presentations	**Zhu, T.** & Minda, J. P. (2021, Nov). Temperament and the Relationship Between Mood and Category Learning. *Talk presented at the 62nd annual meeting of Psychonomic Society* (virtual conference). **Zhu, T.** & Minda, J. P. (2018, July). Evidence for idiom processing advantage of L1 Idioms in an L2. *Talk presented at the 28th annual meeting of the Canadian Society for Brain, Behaviour, and Cognitive Sciences.* St Johns, NL.