Understanding the Mechanisms of Learning:

Findings from behavioural and psychometric studies

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Abstract

Intentional learning refers to goal-directed or motivated acquisition of knowledge, skills, or understanding, which plays an important role in people's daily life. However, much less is understood about the psychometric properties of finer grained factors such as the type and complexity of intentional learning. Moreover, it also remains unclear about the role of personality and other cognitive abilities in intentional learning.

Thus, I first reviewed relevant literature in intentional learning, and then built conceptual models about intentional learning, highlighted the theorical reasoning regarding why personality and cognitive performance are related to intentional learning, and proposed hypotheses in Chapter 1. Then I validated a short version of the Big Five and applied them in people with psychiatric and neurological conditions in Chapter 2. Next, I developed nine internet-based intentional learning tasks that can capture factors including the type (i.e., instruction-based, observational, and model-based) and the complexity (i.e., easy, complex, and model-based) of intentional learning in Chapter 3. Finally, I investigated how personality and cognitive performance are related to intentional learning.

I identified the gap in the literature and the need for psychometric and behavioural investigations of intentional learning in Chapter 1. I found that the short form of the Big Five is a valid measure of personality and can applied to psychiatric and neurological conditions with it being more sensitive to psychiatric conditions comparing to neurological conditions in Chapter 2. In addition, all nine intentional learning tasks I developed has psychometric properties that can be differentiated according to what and how people learn in Chapter 3. Finally, personality and cognitive performance are related to intentional learning, However, these associations were small

and diverse, which may indicate that intentional learning should be treated as a separate set of constructs.

These studies provide psychiatric and behavioral insights into the mechanisms of intentional learning and suggested that intentional learning is not a unitary concept but is consisted of many factors.

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Declaration of Originality

Works presented in this thesis are my own except for these referenced.

Covid-19 Impact Statement

It was originally planned to do imaging work on healthy controls as well as stroke patients to better understand the neural mechanisms of intentional learning. However, due to the limited access to imaging facilities as a result of Covid-19, I had to focus on only behavioral studies that can be conducted online.

Chapter 1 Introduction

1.1. Overview

The aim of this thesis is to understand the psychometric structure that underpins differences in peoples' intentional learning abilities and how they are related to cognition and personality more broadly. This work begins by reviewing the literature and setting up a conceptual framework for testing the psychometrics of different types/complexities of intentional learning and how they are related to personality measures and cognition. Subsequent chapters empirically test this conceptual model, which contributes to a comprehensive thesis.

Specifically, Chapter 1 provides a comprehensive literature review of relevant theories and evidence in this field, develops novel models for subsequent empirical testing, and specifies the aims and hypotheses of each subsequent chapter. Chapter 2 begins by validating the short form of the Big Five Inventory (BFI) that captures personality, which is suitable to be included in a broad online survey with multiple inventories and objective cognitive tasks for assessing personality, as applied in subsequent chapters. Chapter 2 also demonstrated that the short form of the Big Five can be administrated to people with clinical conditions such as psychiatric and neurological illnesses and some dimensions of personality are affected by these conditions, and it is more sensitive to people with psychiatric conditions compared to people with neurological conditions. In Chapter 3, I develop novel computerized learning tasks based on established literature and novel models/theories developed in Chapter 1 and validated the psychometric properties. Chapter 4 tests how personality and various cognitive abilities are associated with factors of intentional learning abilities including how things are learned (i.e., via instruction, observation, and reinforcement) vs. what are learned (i.e., simple, complex, and model-based rules).

Under the overarching aim of learning, the introduction is organized as follows: (1) explanation of the Big Five personality traits, the need for short but yet validated version of the Big Five, and how psychiatric and neurological condition may affect the Big Five, (2) different types of intentional learning and their cognitive and neural mechanisms, and (3) how and why personality is related to learning.

1.2. Big Five personality traits

Personality-based research was based on four assumptions made on human nature including (1) personality traits exist and can be measured, (2) personality traits vary across individuals, (3) individual traits can result in different behaviours, (4) people are able to understand themselves as well as others (McCrae & Costa, 2008). The dimensions of the Big Five personality traits were identified through extensive lexical analysis, which heavily relies on the fourth assumption that people can understand themselves and others. Indeed, an important historical function of language is to help understand the differences between individuals (Allport & Odbert, 1936; John et al., 2008). Over time, languages include words that facilitate the identification of the most silent and lasting individual differences in what people are. Lexical analysis means to gather lists of phrases and adjectives that can be used to describe enduring individual characteristics. In a typical lexical analysis study, participants are required to rate how well each adjective or phrase can describe themselves or another person. Then generally a factor analysis is performed to identify the latent variables or traits that underlie these responses. Although some people might find more (e.g., Ashton & Lee, 2005; Paunonen & Jackson, 2000) or fewer factors (Blackburn et al., 2004; Musek, 2007), generally five factors are consistently identified including Extraversion, Openness, Agreeableness, Conscientiousness, and Neuroticism (sometimes referred by its inversion-Emotion Stability). Moreover, this five-factor structure has been extensively replicated across different language and cultural contexts (see John et al. (2008) for a review) including in unusual subpopulations (Yang et al., 1999).

In addition, these traits seem to be quite stable throughout the life cycle (Caspi et al., 2005; but see Srivastava et al. (2003)), but also, they do change to some degree from time to time (Srivastava et al., 2003). Specifically, according to 'maturity principle,' Agreeableness, and Conscientiousness increases with age, whereas Neuroticism declines (e.g., Mann et al., 2021). Moreover, they are heritable (Bouchard, 1997; Plomin et al., 1990; Van Gestel & Van Broeckhoven, 2003). There is also evidence suggesting that variations in these dispositional factors are associated with the biological makeup. For instance, some studies have identified the associations between specific genetic markers and the Big Five personality traits (Lesch et al., 1996; see Canli (2008) for a review). The Big Five is also related to brain structure. One study has found that the Big Five personality traits are associated with the size of theoretically associated regions of the brain (see also DeYoung et al., 2009). Specifically, DeYoung et al. (2010) found that the trait Conscientiousness is associated with the volume of the lateral prefrontal cortex (LPFC), which is crucial for planning and impulse control.

A large body of batteries has been developed to measure the Big Five personality traits, which each battery contains a list of adjectives (e.g., “temperamental” (Goldberg, 1992)) or phrases (e.g., “Sometimes I do things on impulse that I later regret” (Costa & McCrae, 1992)). Each respondent was asked to rate how well each adjective or phrase describes themselves well. After data collection, researchers calculate scores for each personality trait of the Big Five. There are various instruments that can be used to measure the Big Five personality traits, ranging from inventories that contain only 10 items (i.e., Ten Item Personality Measure (TIPI; Gosling et al., 2003; Langford, 2003) to batteries that are made off dozens of items such as Big Five Questionnaire (BFQ; Caprara et al., 1993), Big Five Inventory (BFI; John et al., 1991), Mini-Markers (Saucier, 1994), NEO-Five-Factor Inventory (NEO-FFI; Costa & McCrae, 1992)) or even hundreds of item (NEO–Personality Inventory–Revised (NEO-PI-R); Costa & McCrae, 1992; International Personality Item Pool (IPIP); Goldberg et al., 2006).

Certainly, there are trade-offs in internal reliability and brevity when choosing which inventory to use in order to measure personality. For instance, the benefit of using scales with dozens of items such as the NEO-PI-R is high internal consistency (Cohen's alpha=0.85; Cost & McCrae, 1992). However, the NEO-PI-R takes more than 30 minutes to complete, making it hard to administrate to measure other variables of interest, and on clinical populations who might not afford such a cognitive burden. By contrast, the TIPI measures the dimensions of the Big Five with only two items. However, TIPI scales have lower internal consistency compared to longer batteries given it has only two items per domain. Thus, the BFI is compromised for its moderate length and reliability and has been widely used in literature.

1.2.1. The need for developing short scale of the Big Five Inventory

Although the widely used BFI (John et al., 1991) is shorter compared to the more extensive inventories such as the NEO–PI–R, it is still too long for some groups of participants (e.g., people with clinical conditions) and to include in a large battery. Indeed, one of the modern research objectives is to develop shortened scales (e.g., Caprara, 1994; Gouveia et al., 2021; Laros et al., 2018; Rammstedt & John, 2007; Saucier, 2007). There is a large amount of empirical evidence suggesting that instruments with a large number of items could be a source of measurement error (Laros et al., 2018). For instance, long instruments could induce discouragement, fatigue, and inattention in the participants, especially making them hard to implement in clinical groups. Furthermore, a huge number of items may impede the joint administration of multiple instruments. Therefore, scales with fewer items that could potentially avoid the problems outlined are favored given they have acceptable reliability and validity (Laros et al., 2018).

Undeniably, the available short version of the scale has many caveats of short measurements including poor reliability and validity (Kruyen et al., 2013; Smith et al., 2000), which is the reason why traditional psychometric inventories consist of a larger number of items, typically 40 items or more. In addition, these long scales are carefully constructed such that every item in the inventory contributes to reliability and sufficient construct coverage with many facets. Leaving out items for established psychometric tests can cause lower reliability and loose construct coverage, which could create estimated group mean and correlation biases (Nicewander & Price, 1983; Sijtsma & Emons, 2011) and impair individual decision-making (Emons et al., 2007; Kruyen et al., 2012).

Indeed, available shortened versions of the BFI are not always validated at large scales with cross-validation which puts them at risk of being invalid and unreliable (Kruyen et al., 2013; Smith et al., 2000). Thus, there is a need for a short but rigorously validated personality inventory suitable for use in different contexts including via online platforms and applying to patients who may have too much cognitive burden if taking the original inventory.

1.2.2. Big Five in populations with psychiatric and neurological conditions

Common psychiatric and neurological disorders may correlate with personality. Four alternative models have been proposed to account for the empirically demonstrated associations between personality and psychopathology, including the predisposition/vulnerability model, complication/scar model, pathoplasty/exacerbation model, and the spectrum model (Krueger & Tackett, 2003; Nigg, 2006; Tackett, 2006; Whittle et al., 2006). The predisposition/vulnerability model suggests that particular traits confer a greater risk for the development of a psychological disorder (Krueger & Tackett, 2003; Tackett, 2006). Conversely, the complication/scar model proposes that the development of psychological disorders alters an individual's premorbid personality (Tackett, 2006; Whittle et al., 2006). According to the pathoplasty/exacerbation model, the etiology of psychological disorders is independent of traits. However, premorbid temperament traits are purported to influence the manifestation, severity, and course of mental illness (Tackett, 2006; Whittle et al., 2006). The spectrum model conceptualizes a dimensional relationship between temperament/personality and psychopathology, such that psychological disorders represent extreme poles of the continuum of individual differences in temperament (Krueger & Tackett, 2003; Nigg, 2006; Tackett, 2006).

Compared to personality-psychiatry associations, the relationships between neurological conditions and personality are much less understood. One might suspect that there are some relationships between them because personality traits are closely related to brain structures and neurological conditions are characterized by brain damages. For instance, one study identified that the Big Five personality traits are associated with the size of theoretically associated regions of the brain (see also DeYoung et al., 2009). DeYoung et al. (2010) found that Neuroticism is associated with brain regions that are related to threat, punishment, and negative affect. Specifically, Neuroticism is negatively associated with dorsomedial prefrontal cortex and in portions of the left medial temporal lobe, including the posterior hippocampus, portions of basal ganglia and midbrain, including globus pallidus and bilateral subthalamic nuclei, and regions in the right precentral gyrus (DeYoung et al., 2010). In addition, brain regions that have associations with Neuroticism were found in bilaterally in the mid-cingulate cortex, extending into the white matter of the cingulate gyrus and, in the left hemisphere, into the caudate as well as one region in the middle temporal gyrus and one in the cerebellum (DeYoung et al., 2010). Agreeableness is associated with the volume of brain regions that process information associated with others (e.g., the retrosplenial region of posterior cingulate cortex (PCC), superior temporal sulcus, adjacent superior temporal gyrus, and fusiform gyrus). Conscientiousness is associated with the volume of the LPFC, which is a brain region that is associated with planning and controlling behaviour (DeYoung et al., 2010). Extraversion is associated with the volume of the medial orbitofrontal cortex, which is a brain region involved in reward information processing (DeYoung et al., 2010).

1.2.3. The purpose and hypothesis of Chapter 2

Thus, the purpose of Chapter 2 is to validate the short version of the Big Five and determine how personality traits are affected by psychiatric (N=19,185) and neurological conditions (N=4,162). I hypothesise that the “little” Big Five is a valid measure of personality as indicated by good part-to-whole correlation and test-rest reliability but just with 18-items and the “little” Big Five can be used to assess personality traits in people with psychiatric and neurological conditions. However, the patterns of personality traits may differ by specific conditions.

1.3. Learning

Learning has been systematically studied for as long as psychology has been regarded as an independent science (e.g., Ebbinghaus, 1885; Thorndike, 1911). During the most part of the last century, it has been arguably the most studied topic in psychology (De Houwer et al., 2013). At present, modern scientists are trying to address learning-related questions in all areas of psychology such as experimental psychology, personality psychology, and cognitive neuroscience. This presents a large and fractured literature. Therefore, it is important to define what "learning" really is. Indeed, it has been observed that few researchers are explicit about what they really mean about the term "learning" (De Houwer et al., 2013). Even influential textbooks do not contain a clear definition of their subject matter (e.g., Bouton, 2007; Schwartz et al., 2002). Perhaps this matter has a basis in there being no general consensus regarding the definition of learning (De Houwer et al., 2013). It has been argued that there are two main ways of defining learning: (1) a simple functional definition of learning, and (2) a mechanistic definition of learning.

As first noticed by Lachman (1997), textbooks usually define learning as a change in behaviour with experience. In other words, learning is defined as the effect of experience on behaviour. However, many researchers argued that such a simple definition of learning is not satisfactory (e.g., Domjan, 2010; Lachman, 1997; Ormrod, 1999, 2008). Specifically, there seem to be two points of counterevidence against this definition: (1) evidence from latent learning research has suggested that learning does not necessarily require changes in behaviour to occur (De Houwer et al., 2013). (2) observing changes in behaviour does not provide sufficient evidence that learning is occurring because not all effects on behaviour changes precipitate learning and not all changes in behaviour require learning. For example, certain individual experiences (e.g., the occasion of an unexpected stimulus such as a loud sound) could result in an immediate but transient change in behaviour.

The mechanistic definition suggests that some aspects of the learning process operate at the time of behaviour change (De Houwer et al., 2013). In other words, the mechanistic approach emphasizes the presence of a contiguous cause of behaviour: if a behavioural change happens at time 2, then there must be an element that caused this behavioural change before time 2 (Chiesa, 1992). However, the phenomenon of latent learning challenges the mechanistic definition of learning. The experience at time 1 is assumed to cause the change in behaviour at time 2 but does not immediately present before that change in behaviour occurs (De Houwer et al., 2013). To solve this controversy, it is typically assumed that learning can occur in a manner that is not immediately expressed but then has an effect on behaviour, with this linkage being, therefore "latent." Thus, the mechanistic approach seems to define learning in terms of changes in behaviour in the organism.

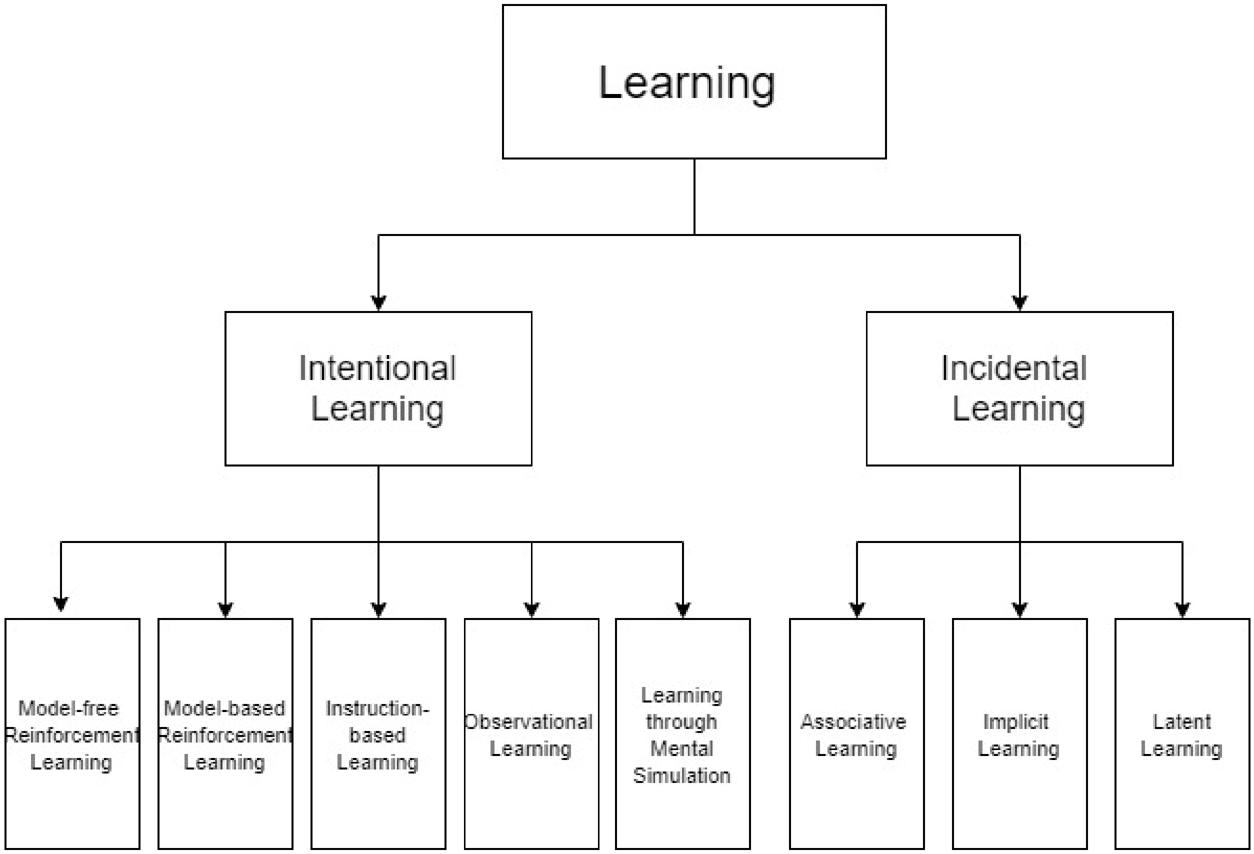
However, there are also some shortcomings associated with the mechanistic definition of learning. The assumption that the change in behaviour is not necessary nor efficient to infer learning suggests that changes in behaviour do not signal learning. Rather, proving a mechanistic definition of learning requires the presence of some kind of changes in the organism that is caused by some kind of experience. This is difficult because it is hard to identify what exact change in behaviour of that organism is the result of an experience and how one can determine this change has occurred. Hence, a mechanistic definition of learning makes it difficult to identify and study learning in some contexts (De Houwer, 2011).

A simple functional definition of learning is criticized as being too overtly inclusive (e.g., including changes in behaviour as a result of a single presentation of a stimulus, such as a loud voice) and not inclusive enough (e.g., excluding latent learning). By contrast, the mechanistic definition of learning could be considered an appropriate scope, but it is hard to verify. De Houwer et al. (2013) has proposed a definition of learning that overcomes the problem of both a simple functional definition of learning and a mechanistic definition of learning: learning is an ontogenetic adaptation, which is the change in the behaviour of an organism resulting from the regularities in the environment of that organism. Specifically, there are three components in this definition: (1) changes in the behaviour of that organism, (2) regularity in the environment of that organism, (3) a causal relation between (1) and (2).

1.3.1. Different types of learning

Learning in general can be classified as intentional learning and incidental learning. Intentional learning can then be divided into five major categories: model-free reinforcement learning (RL), model-based RL, instruction-based learning (IBL), observational learning (OL), and learning through mental simulation. Incidental learning consists of three main types of learning: classical conditioning, implicit learning, and latent learning (Figure.1).

Figure.1. Different types of learning. Learning can be mainly put into two categories including intentional learning and incidental learning. Intentional learning includes model-free reinforcement learning, model-based reinforcement learning (RL), instruction-based learning (IBL), observational learning (OL), and learning through mental simulations whereas incidental learning is consisted of associative learning, implicit learning, and latent learning.



1.3.1.1. Intentional learning

Intentional learning is generally defined as goal-directed or motivated acquisition of knowledge, skills, or understanding. Intentional learning gained particular attention as a result of the seminal work of Bereiter and Scardamalia (1989) on computer-supported intentional learning environments. Bereiter and Scardamalia (1989) intentional learning to cognitive operations that consider learning as a goal rather than an incidental outcome. The assumption under this definition is that learning could be an incidental outcome, but only some cognitive activities are implemented according to procedures that contain motivations and goals. The prerequisite for the occurrence of learning may depend on both situational and intrinsic factors regarding what situation affords goal-attainment opportunities and what the learner's cognitive resources are to achieve these goals.

1.3.1.1.1. Instruction-based Learning (IBL)

IBL (sometimes also termed as rapid instruction-based task learning, "RITL") is the ability to learn to perform tasks based on explicit instructions rapidly. Instruction-based learning relies on the flexibility of cognitive systems, which enables humans to rapidly adapt to temporal programs for implementing non-automated tasks in a controlled manner (Hampshire et al., 2016). Humans often use IBL to learn how to perform new tasks, such as how to use coffee machines, how to cook a new dish, and how to play new computer games. IBL has evolutionary advantages because it can avoid the cost of choosing the wrong action and allow communication between learners.

1.3.1.1.2. Model-based reinforcement learning (RL)

Tasks also can be learned from RL, where participants learn from receiving feedback (Cole et al., 2013). In RL, the objective of an agent is to maximize the rewards obtained in the future, and it is achieved by improving its action selection from outcomes associated with that action. Model-based RL generates goal-directed actions in the environment by employing a model or a cognitive-style representation (Daw et al., 2005). This internal model supports the prospective assessment of the consequences of taking a particular action (Dayan & Berridge, 2014). Specifically, in the model-based system, a cognitive model or map of the environment is required, which illustrates how different "states" or situations of the environment are connected with each other. Values for different action paths through the environment can then be computed by a kind of mental simulation analogous to planning these actions (Gläscher et al., 2010). A real-life example of model-based RL would be the scenario where one wants to make a travel plan. Specifically, one must build a mental model of the environment (the city and its attractions), define a reward function (enjoyment), and plan one's actions (itineraries) based on simulations and predictions from one's model.

1.3.1.1.3. Model-free reinforcement learning (RL)

By contrast, unlike model-based RL, model-free RL learns action values directly by trial and error without building such a model of the environment (Gläscher et al., 2010). In model-free systems, the agent merely learns by caching information about the utilities of the outcome encountered in the past with the environment, which generates direct rules of how to behave or what actions to choose based on the predictions of the long-run value of actions (Dayan & Berridge, 2014). Model-free values are regarded as being free-floating, given they can become detached from any specific outcomes (Gläscher et al., 2010). A real-life example would be if one learns to play a new video game. One plays better based on feedback one receives while exploring the game.

1.3.1.1.4. Observational learning (OL)

OL refers to learning by watching others' actions and outcomes in certain circumstances. Unlike imitation, observational learning does not just require the learning to replicate an action (Kang et al., 2022). Rather, the learner has to transfer the observation into actions as close as possible to the performer's action, whom the learner learned from. Specifically, the goals must be achieved, and the response must be made correctly (Torriero et al., 2007). This ability to learn from observed actions and outcomes is crucial for many species when the stakes are high. For example, predators can avoid eating poisonous prey by watching others eating novel food without trying it (Burke et al., 2010). Observational learning involves (1) inferring others' attention in terms of goals to be achieved from observation, and (2) processing other's stimulus-response-outcome (S-R-O) associations that can be later used to select behaviours towards wanted outcomes. Learning how to dance, how to play a new musical instrument, and how to paint involves this type of learning.

1.3.1.1.5. Learning through mental simulation

Learning through mental stimulation (sometimes referred to as motor imagery in the literature) is defined as an active type of learning by reproducing the representation of a specific action within working memory, without producing any explicit motor output (Decety & Grèzes, 1999). There is growing interest in studying this cognitive process and clarifying the relationship between imagined and executed actions. For example, some studies have suggested that mental practice improves the learning of motor skills (Jackson et al., 2003). Indeed, results from sport psychology and skill-learning research have shown that mental practice improves participants' performance compared to no-practice control conditions (Driskell et al., 1994). Together, these findings suggest that mental simulation is effective in the acquisition of novel knowledge/skills. A real-life example would be when one is preparing for an important competition, such as an Olympic event. The athlete mentally simulates their performance before the actual event.

1.3.1.2. Incidental learning

The definition of incidental learning is typically interpreted in common terms, rather than firmly rooted in a particular theory. According to Schmidt (1994), there are three ways of defining incidental learning: (1) learning without the intention to learn (Schmidt, 1994). (2) Learning one stimulus aspect while paying attention to other stimuli aspects. As Schmidt points out, incidental learning is “learning of one thing (…) when the learner’s primary objective is to do something else (…)” (Schmidt, 1994, p. 16). (3) Learning of formal features through a focus of attention on semantic features. Again, according to Schmidt (1994, p.16), incidental learning is “learning of one thing (e.g., grammar) when the learner’s primary objective is to do something else (e.g., communicate).” More recently, Gass (1999) defined incidental learning with a more extended meaning as learning of grammatical structures without being exposed to the instances of these structures. Gass (1999) referred to two studies on the acquisition of relative clauses (Gass et al., 1988) in which learners were exposed to some but not all relative clauses, but they learned not only structures presented to them, but also structures implied by ones that were presented “incidentally.” Thus, one could speculate incidental learning as learning of not presented, not attended but implied stimuli, similar to the notion of learning an exemplar, as per literature on neural networks. To have a uniform definition in the current review, I simplify incidental learning as learning that is neither motivated nor unintended.

1.3.1.2.1. Associative learning

Associative learning requires the ability of living organisms to perceive the contingency between two relations in the environment. One well-known experimental procedure in psychology could be used to study association learning: classical conditioning and operant conditioning. Classical conditioning was introduced by Pavlova and his dogs. Pavlova found that the dogs salivate when the bell rings even though without the presence of the food after food and the sound of the bell presented together for a few times (training). The salivation in response to the actual smell/taste of food is an unconditioned response (UR) because it occurs through a natural reflex without any prior training, and the food is an unconditioned stimulus (US). When the sound of the bell and food pairs with the taste/smell of the food, then the bell becomes the conditioned stimulus (CS), and the salivation when hearing the bell becomes the conditioned response (CS).

1.3.1.2.2. Implicit learning

Implicit learning refers to learning complex information without complete awareness of what has been learned (Seger et al., 1994). Implicit learning had become an area of study since A.S. Rebel's work on artificial grammar learning in the late 1960s. Moreover, the interest in implicit learning expanded in the last decade, beginning with Broadbent and colleagues' work regarding the dynamic system research in the early 1980s (Berry & Broadbent, 1984), and continued with research on contingent reaction time task (Lewicki et al., 1987) and serial reaction time task (Nissen & Bullemer, 1987).

1.3.1.2.2.3. Latent learning

Latent learning is usually associated with animal learning research. In a latent learning experiment, an animal is placed into a novel experiment, and they are allowed to explore. Typically, there is food and water at some locations when the animal is neither hungry nor thirsty. Later, when the animal can find food or water quickly although the animal has not been pre-expose to the way of finding water or food reward. This idea challenges the well-known reinforcement learning models, which Tolman termed pejoratively as the "stimulus-response school" (Wang & Hayden, 2021).

1.3.2. Neural basis for intentional learning

There is a large body of literature regarding neural mechanisms of various forms of intentional learning. Noticeably, pairs of intentional learning conditions are typically studied together with one as a control condition and the other as an experimental condition depending on the research question (e.g., Burke et al., 2010; Hampshire et al., 2016; Morfardini et al., 2008, 2013). For example, Burke et al. (2010) and Morfadini et al. (2008, 2013) compared the neural systems recruited during both observational learning and model-free trial-and-error reinforcement learning. They identified several common and distinct networks. Similar approaches are used in Hampshire et al. (2016), who compared the brain activation patterns between instruction-based learning and model-free trial-and-error reinforcement learning; and also in Gläscher et al. (2010), who compared the neural mechanisms of model-based-reinforcement learning with model-free reinforcement learning. Different studies have reported different areas are activated even using the same kinds of tasks that intend to measure the same types of intentional learning, thus the exact neural representation of intentional learning remains debated.

1.3.2.1. Observational learning (OL)

Previous studies have found that the superior and inferior parietal lobes, premotor dorsal cortex bilaterally, the left dorsal striatum, the anterior ventrolateral, dorsolateral prefrontal cortex (DLPFC), the supplementary motor area (SMA), and the cerebellum bilaterally were involved in acquiring rules (i.e., when participants watched the actor demonstrating how to perform the visuomotor tasks; Monfardini et al., 2013). The right ventrolateral and anterior frontal cortices, pre-SMA (pre-supplementary motor area), parietal cortex, the right pars triangularis (BA45), the right inferior parietal lobule, and the posterior visual areas were involved when retrieving newly acquired rules (Monfardini et al., 2008). The middle cingulate cortex bilaterally in the middle cingulate cortex, the anterior insula, the posterior medial frontal cortex (pMFC), and the posterior temporal sulcus (pSTS; Monfardini et al., 2013) were recruited during the execution of the learned rules.

1.3.2.2. Instruction-based learning (IBL)

Previous studies have found that IBL results from the interplays of many brain regions including the ventrolateral prefrontal cortex (VLPFC), DLPFC, anterior cingulate cortex (ACC), caudate, premotor cortex (PMC), striatum, caudate, parietal cortex, anterior insula, the temporal parietal junction (TPJ) bilaterally, the inferior frontal sulcus (IFS) during instruction based learning (Cole et al., 2010; Hampshire et al., 2016, 2019; Harstra et al., 2011; Ruge et al., 2019; Ruge & Wolfensteller, 2010, 2013).

1.3.2.3. Model-free reinforcement learning (RL)

In the context of classical model-free RL research, the reward prediction error (RPE) measures the differences between the actual and expected reward at particular status. Studies have established the relationship between the RPE and brain regions including the ventral tegmental area, substantia nigra pars compacta, and the ventral striatum (Gläscher et al., 2010). Several studies have found that the reward prediction error signals were associated with subcortical structures such as the striatum (Gläscher et al., 2010; Schultz, 1998; Schultz et al., 1997).

Other than these regions, model-free RL also engages common brain regions that support reinforcement learning, including the posterior parietal cortex (PPC; Dorris & Glimcher, 2004; Platt & Glimcher, 1999; Seo et al., 2009; Sugrue et al., 2004), DLPFC (Barraclough et al., 2004; Kim et al., 2008), premotor cortex (Churchland et al., 2006; Pastor-Bernier & Cisek 2011), medial frontal cortex (Seo et al., 2009; Seo & Lee 2007; So & Stuphorn, 2010; Sul et al. 2010), the primary motor cortex (Georgopoulos et al., 1986), frontal eye field (Hanes & Schall, 1996), supplementary eye field (Schlag & Schlag-Rey, 1987), PPC (Andersen et al., 1987), superior colliculus (Schiller & Stryker, 1972; Wurtz & Goldberg, 1972), lateral habenula (Matsumoto & Hikosaka, 2007), globus pallidus (Hong & Hikosaka, 2008), ACC (Matsumoto et al., 2007; Seo & Lee, 2007), orbitofrontal cortex (Sul et al., 2010), striatum (Cai et al., 2011; Kim et al., 2009; Lau & Glimcher, 2008; Oyama et al., 2010; Samejima et al., 2005), and amygdala (Hsu et al., 2005; Huettel et al., 2006).

1.3.2.4. Model-based reinforcement learning (RL)

Model-based RL action valuation requires the learner to predict what state is currently expected given the learner knows the previous states and choices. State prediction error (SPE) could be used to learn these expectations, which represents the surprise in the new states given the current estimations of state-action-state transition probabilities (Gläscher et al., 2010). It has been suggested that SPEs can be seen in the LPFC (lateral prefrontal cortex; Gläscher et al., 2010; Samejima & Doya, 2007).

Other than these regions, model-based RL involves the PPC (Dorris & Glimcher, 2004; Platt & Glimcher, 1999, Seo et al., 2009; Sugrue et al., 2004), DLPFC (Barraclough et al., 2004; Kim et al., 2008), premotor cortex (Churchland et al., 2006; Pastor-Bernier & Cisek, 2011), medial frontal cortex (Seo & Lee, 2007; Seo et al., 2009; So & Stuphorn, 2010; Sul et al., 2010), the primary motor cortex (Georgopoulos et al., 1986), frontal eye field (Hanes & Schall, 1996), supplementary eye field (Schlag & Schlag-Rey, 1987), PPC (Andersen et al., 1987), superior colliculus (Schiller & Stryker, 1972; Wurtz & Goldberg, 1972), lateral habenula (Matsumoto & Hikosaka, 2007), globus pallidus (Hong & Hikosaka 2008), ACC (Matsumoto et al., 2007; Seo & Lee, 2007), orbitofrontal cortex (OFC; Sul et al., 2010), striatum (Cai et al., 2011; Kim et al., 2009, Lau & Glimcher, 2008; Oyama et al., 2010; Samejima et al., 2005), and amygdala (Hsu et al., 2005; Huettel et al., 2006).

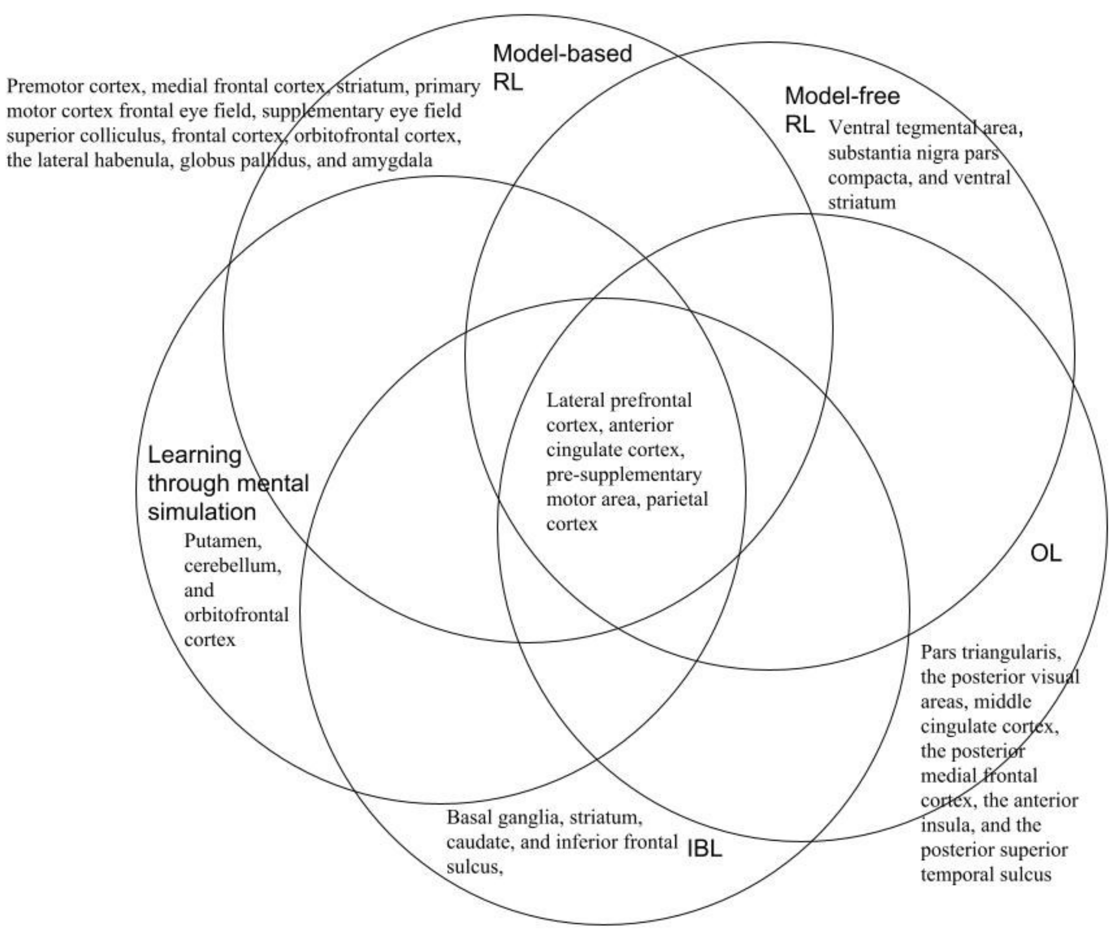
1.3.2.5. Learning through mental simulation

A recent meta-analysis found that learning through mental simulation primarily engages a network of brain areas including bilateral premotor, rostral inferior and middle superior parietal, basal ganglia, and cerebellar regions (Hardwick, 2018). There were two large bilateral premotor clusters spanning the SMA-proper and pre-SMA, extending to the dorsal and ventral premotor cortices (Hardwick, 2018). The left premotor cluster included areas of the cingulate and putamen. Two bilateral parietal clusters also spanned the inferior and superior bolubes with a right-lateralized activation pattern in the inferior parietal sulcus (Hardwick, 2018). Further subcortical clusters were found bilaterally in lobule VI of the cerebellum (Hardwick, 2018). Moreover, this was a relatively small cluster in the left middle frontal gyrus, which is consistent with the location of the dorsolateral prefrontal cortex (Al-Hakim et al., 2006).

1.3.3. An anatomical model of intentional learning

As discussed, studies have compared different types of intentional learning and have found both common and distinct patterns of activation profiles. I summarised them in Figure.2. Noticeably, these common regions include LPFC, ACC, pre-SMA, and the parietal cortex. These regions in turn are part of the multiple-demand (MD) system (Duncan, 2010).

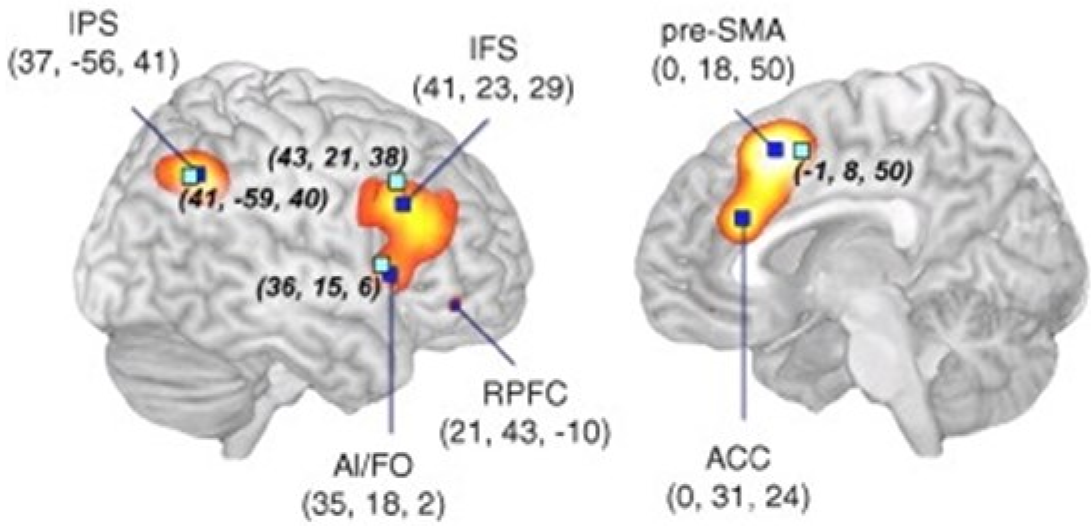
Figure. 2. Common and distinct brain regions engaged in different types of intentional learning. This figure is made of five circles that represent each type of intentional learning. The brain regions in the very middle represent the common brain regions of all types of intentional learning whereas brain regions in the circles represent the brain regions are distinct for each type of intentional learning.



1.3.3.1. The multiple-demand (MD) system

The common brain regions activated in different intentional learning tasks across studies are part of the MD system (Figure.2), which is a system that activates in various forms of cognitive tasks, assembles novel tasks (Duncan, 2010), and can be used to predict fluid intelligence (Woolgar et al., 2010). This suggests that intentional learning in various forms may primarily reflect the operation of the same underlying brain system (Hampshire et al., 2016; Sliwinska et al., 2017). A corollary of this is that individual and cross-group variability in intentional learning may accord closely with a single overarching cognitive ability, which in turn, spans cognition more broadly. Moreover, the multiple demand is not monolithic but has specialised sub-regions/ sub-networks. Dimensions of cognitive ability appear to reflect those sub-networks. It may be that intentional learning is multi-factor in terms of abilities, but that these converge with factors of cognitive ability/intelligence more generally (e.g., Hampshire et al., 2012).

Figure.3. The multiple-demand (MD) system. The multiple-demand system consists of sets of brain regions in the prefrontal cortex and the parietal cortex, including the cortex in and around the posterior part of the inferior frontal sulcus (IFS), the cortex in the adjacent operculum and the anterior insular (FO/AI), the cortex in the adjacent dorsal anterior cingulate and the pre-supplementary motor area (ACC/SMA), and the cortex in around the intraparietal sulcus (IPS). Adapted from Duncan (2010) under AB CC.



1.3.3.1.1. The roles of each commonly recruited region in intentional learning

The LPFC is primarily responsible for cognitive control where a large degree of flexibility is required (Miller & Cohen, 2001), which include several cognitive processes like working memory, attentional selection and planning. By definition, intentional learning requires an agent to adapt the rule flexibly. Thus, learning a novel task could be one of the best examples of cognitive flexibility possible (Cole et al., 2013). This impressive mental flexibility in IBL is made possible due to the rapid transfer of practiced rule representations within LPFC to novel contexts (Cole et al., 2011).

The ACC has been implicated in several complex cognitive functions like empathy, inhibitory control, emotion, and decision-making. In intentional learning, previous research has found the activities of the ACC in response conflict monitoring during novel and non-automatic learning tasks (e.g., Abutalebi et al., 2012; Kerns et al., 2004). Kerns et al. (2004) found that the ACC activation could predict subsequent improvements in behaviour on tasks that measure cognitive control. Moreover, Becker et al. (2016) found the involvement of ACC during novel task execution.

The pre-SMA was initially recognized when applying electrical stimulation to this region evokes movement in humans. It has been suggested that the pre-SMA plays a critical role in exerting control over voluntary actions (Nachev et al., 2007), which is involved in language generation (Binder et al., 1997; Wise et al., 1991), movement recognition and ideation (Grafton et al., 1996; Stephan et al., 1995), maintaining working memory (Pollmann & von Cramon, 2000), establishing visuomotor associations (Sakai et al., 1999), learning and performing movement sequences (Hikosaka et al., 1996; Kawashima et al., 1998; Isoda & Tanji, 2004; Nakamura et al., 1998; 1999; Sakai et al., 1998; Shima & Tanji, 1998, 2000), time perception and discrimination (Coull et al., 2004; Pastor et al., 2006), "internally" guided action (Deiber et al., 1991; Frith et al., 1991; Hadland et al., 2001; Lau et al., 2006), representing action intentions (Lau et al., 2004), conflict resolution or monitoring (Garavan et al., 2003; Nachev et al., 2005; Ullsperger & von Cramon, 2001), and switching between action sets (Kennerley et al., 2004; Matsuzaka & Tanji, 1996; Rushworth et al., 2002; Shima et al., 1996). Indeed, intentional learning requires changes in behaviour and most learning tasks ask participants to make a choice by moving their body parts as the evidence of learning.

The parietal cortex has been indicated to play a central role when focusing attention on behaviourally relevant information that is detected through sensory inputs. Brain regions within the parietal cortex interact with sensory processing areas in the brain to select and enhance behaviourally relevant information, which is also available to other brain regions for planning and executing these physical movements (Posner & Dehaene, 1994). Moreover, patients with damage to the parietal cortex tend to have a syndrome called 'neglect,' which could result in a bias in selecting information and planning movements. In addition, the parietal cortex has also been implicated in building and modifying a mental template for task implementation (Becker et al., 2016). For instance, research has found that the activity of the parietal cortex was proportional to the number of operations being calculated when completing tasks involving arithmetic (Danker & Anderson, 2007; Stocco & Anderson, 2008). Thus, the parietal cortex is believed to play a role for building and updating the task model and updating information in working memory by communication with the DLPFC and striatum (Stocoo et al., 2010, 2012).

1.3.3.2. Distinct regions in different types of intentional learning

Besides commonly recruited MD system, different types of intentional learning may recruit additional brain regions depending on the type of intentional learning. Model-based and model-free RL may share some brain systems that are different from other types of intentional learning. This section compares these differences.

1.3.3.2.1. Model-based reinforcement learning (RL)

The brain regions that support both model-based and model-free RL could be divided into several subcategories: (1) brain regions that calculate values functions, (2) brain regions that are responsible for selecting actions, and (3) brain regions that update value functions (Lee et al., 2012). Studies have found neural activities that relate to value functions in various brain regions, including the PPC (Dorris & Glimcher, 2004; Platt & Glimcher, 1999; Seo et al., 2009; Sugrue et al., 2004), DLPFC (Barraclough et al., 2004; Kim et al., 2008), premotor cortex (Pastor-Bernier & Cisek, 2011), medial frontal cortex (Seo & Lee, 2007; 2009; Sul et al., 2010; So & Stuphorn, 2010), and striatum (Cai et al., 2011; Kim et al., 2009; Lau & Glimcher, 2008; Samejima et al., 2005). Previous research has found that selecting actions are tightly connected with neuronal activities in a set of brain regions, including the primary motor cortex (Georgopoulos et al., 1986), premotor cortex (Churchland et al., 2006), frontal eye field (Hanes & Schall, 1996), supplementary eye field (Schlag & Schlag-Rey, 1987), PPC (Andersen et al., 1987), and superior colliculus (Schiller & Stryker, 1972; Wurtz & Goldberg, 1972). Brain areas for updating value functions include PFC and PPC (Barraclough et al., 2004; Seo & Lee, 2007; Seo et al., 2009), frontal cortex, striatum (Kim et al., 2007; 2009; Sul et al., 2010; 2011), OFC (Abe & Lee, 2011; Barraclough et al., 2004; Kim et al., 2009; Seo & Lee 2007, Roesch et al., 2009; Sul et al., 2010), the lateral habenula (Matsumoto & Hikosaka, 2007), globus pallidus (Hong & Hikosaka, 2008), ACC (Matsumoto et al., 2007; Seo & Lee, 2007), and amygdala (Hsu et al., 2005, Huettel et al., 2006).

It has been suggested that value-related activities in the medial prefrontal cortex relate to model-based reinforcement learning as indicated by the SPE (Hampton et al., 2006; Hampton et al., 2008; Valentin et al., 2007), where others argue that model-based reinforcement learning is based on model-free reinforcement learning (Daw et al., 2011). It is certainly possible that model-based reinforcement learning is just learning a model using model-free reinforcement learning strategies. Thus, the activities found in LPFC in previous studies might not reflect something unique about model-based reinforcement learning per se but reflect model-based learning where a great level of global flexibility is required in general.

1.3.3.2.2. Model-free reinforcement learning (RL)

Previous research from single-unit electrophysiological recordings in monkeys (Bayer & Glimcher, 2005; Schultz, 1998; Schultz et al., 1997) and BOLD signals in humans (D'Ardenne et al., 2008) has found that dopaminergic neurons located in the ventral tegmental area and substantia nigra pars compacta showed a strong activity pattern, which is consistent with the model-free appetitive RPE. Moreover, the BOLD signals from human fMRI have also demonstrated a response profile consistent with dopaminergic inputs in the ventral striatum (Delgado et al., 2000; 2008; Knutson et al., 2001, 2005), also correlates with model-free RPEs (Haruno & Kawato, 2006; McClure et al., 2003; O'Doherty et al., 2003).

1.3.3.2.3. Observational learning (OL)

During rule retrieval, OL recruits additional regions including the right pars triangularis (BA 45) and the posterior visual areas. Monfardini et al. (2008) identified more activities in the right pars triangularis during retrieval than during movie watching and identified similar BOLD signals when subjects retrieved motor responses associated with a visual arbitrary stimulus. This finding is consistent with the role of the pars triangularis in observation of actions, but not in imitation or execution of actions (Molnar-Szakacs et al., 2005; Kang et al., 2022). The role of posterior areas may be the result of top-down modulation. Specifically, in Monfardini et al. (2018), participants must pay attention to the hand. At the same time, a retrieval process might reactivate the observed movements during the learning process and the top-down modulation might then influence distinct visual areas (Kang et al., 2022). During application, observational learning recruits additional brain areas including the middle cingulate cortex (MCC), the posterior medial frontal cortex (pMFC), the anterior insula, and the posterior superior temporal sulcus (pSTS). Previous research has demonstrated that the MCC plays an important role in monitoring other’s decisions (Apps et al., 2013), and the pMFC and the anterior insula are both part of the error-monitor network (Radke et al., 2011). An observational learning study by

Monfardini et al. (2013) has also suggested that the pMFC is highly involved in self's and other error-monitoring and subsequent behavioural adjustments. The anterior insular cortex is involved in both performance monitoring processes (Radke et al., 2011) and the autonomic responses to error in non-social contexts (Ullsperger & von Carmon, 2003). Moreover, its level of activity increases with error awareness (Ullsperger et al., 2010; Klein et al., 2007). The role of the posterior superior temporal sulcus (pSTS) is processing of others' errors during observational learning (Kang et al., 2022).

1.3.3.2.4. Instruction-based learning (IBL)

IBL recruits additional brain regions including the caudate, striatum, and the IFS. It has been suggested that IBL begins with rapid updating of information in working memory, which is a process dependent on dopamine and/or basal ganglia signals (Cole et al., 2013). Moreover, the caudate is engaged in the gating of information for rapid updating of mental representations (O'Reilly & Frank, 2006). Thus, I hypothesise that the role of this region during IBL is updating S-R mappings. The striatum has been implicated to associate with learning and rule application (Muhammad et al., 2006). For example, during the application of novel tasks, when a high degree of cognitive flexibility is sought, the striatum seemed to be responsible for controlling the selection of appropriate task-specific variables and dynamically coordinating (i.e., "gating") the information being sent from cortical processing centers to the prefrontal cortex (O'Reilly & Frank, 2006). The IFS belongs to part of the MD system, one previous study has found that the right IFS is specially activated when new instructions are implemented compared to when new instructions are memorized (Demanet et al., 2016). Moreover, Demanet et al. (2016) also found the activities in this region are correlated with the task performance, which is consistent with the role of IFS in acquisition and application of arbitrary S–R associations (e.g., Grol et al., 2006; Loh et al., 2008).

1.3.3.2.5. Learning from mental simulation

One recent meta-analysis found that learning through mental simulation primarily relies on a premotor-parietal network, with involvement of subcortical regions including the putamen and cerebellum (Hardwick, 2018). The putamen is a region within the basal ganglia that acts as an important node of the cortico-striatal sensorimotor circuits (Voon et al., 2015). Moreover, putamen is closely related to automatic movement behaviours (Ashby & Crossley, 2012). Previous studies have found that activities in the putamen correlates with the speed and extent of executed movements (Turner et al., 2003), which is consistent with the involvement of the basal ganglia in calculating the costs of movements (Shadmehr & Krakauer, 2008). This is evident in Parkinson's patients who become slower to move due to dysfunctions of the basal ganglia, which also leads to increases in the duration of imagined movements (Helmich et al., 2007). Thus, one could speculate that the putamen is also involved in regulating the speed of self-paced imagined or executed actions. The cerebellum, in particular the right cerebellar lobule VI is engaged during learning through mental simulation, which accords to the nature of the right cerebellar cluster and is consistent with the function of the cerebellar-thalamo-motor connectivity (Buckner et al., 2011; Daskalakis et al., 2004). The cerebellar lobule VI contains body representations that are not the most prominent during movement execution (Schlerf et al., 2010). However, Harwick et al. (2018) found little evidence of somatotopic involvement of the cerebellum, which suggests that the function for which the cerebellum is recruited differs from learning through mental simulation and actual implementation. Indeed, improved learning performance due to mental simulation relates to increased activities in the medial part of OFC but decreased activity in the cerebellum (Jackson, 2003).

1.3.3. Complexity effects in learning

Task complexity is one of the important factors that influence human behaviour and performance both in real-life scenarios and in the laboratory. For instance, in decision-making research, even if people pretended to integrate possibilities, Tversky and Kahneman (1981) found that the maintained intricacy of practical problems in decision tasks would prohibit them from doing so. Payne (1976) discovered that task complexity was a key determinant of decision process and strategy: decision-makers used a compensatory decision process (a method that involves identifying a set of attributes applicable to the decision, assigning relative importance or weight to each attribute, computing an overall score for each option based on the attribute weight, and selecting the option with the best score) when faced with a low-complexity task, whereas they used a non-compensatory process and focused on selective information when faced with a high-complexity task. Lussier and Olshavsky (1979) and Kim and Khoury (1987) found similar results. In the goal-setting area, involving the development of an action plan designed in order to motivate and guide a person or group toward a goal, Wood et al. (1987) and Campbell (1991) identified task difficulty as a consistent moderator of the goal-setting effect. In this case, the goal-setting system represents a decision-making process designed to effectively achieve self-determined objectives through a series of action and behaviour strategies to be performed. They concluded that goal setting improves task performance the most for low-complexity tasks and the least for high-complexity tasks (Wood et al., 1987; Campbell, 1991).

The effect of task complexity on performance has been examined in intentional learning as well (Dumontheil et al., 2012; Ruge et al., 2019; Parkin et al., 2021). For instance, goal neglect refers to a kind of performance failure that the subject can tell exactly what they should do, but yet makes no attempt to do so (Duncan et al., 2008). This phenomenon could be demonstrated by a complex version of the IBL task (e.g., the feature matching task). This phenomenon relates to task complexity. Inspired by this idea, here I consider several possibilities that intentional learning could go wrong. I propose that to successfully learn, one must perform well in each stage of intentional learning. For example, if one fails to encode rules properly into working memory, then they will misbind rules (Parkins et al., 2021), which if applied consistently can lead to below-chance performance.

There are three levels of task complexity in intentional learning research including: simple S-R associations, complex S-R associations, and model-based S-R associations. Compared to simple S-R associations, complex S-R associations have more pairs of S-R associations to be encoded and applied in learning tasks (Ruge et al., 2019; Parkin et al., 2021). Just like the above mentioned and widely investigated model-based and model-free RL, model-based learning involves building a model of the environment (Gläscher et al., 2010), which is arguably more complex than simple and complex S-R associations.

1.3.4. The purpose and hypothesis of Chapter 3

Thus, the purpose of Chapter 3 is to test the within and between-subject effects of various types of learning including IBL, RL, and OL. I hypothesise that (1) there is a clear within-subject learning effect across different tasks as indicated by increased accuracy but decreased reaction time (RT) with practice, and (2) there are multiple between-subject factors related to intentional learning that can be explained by individual differences in the ability to cope with the type of intentional learning process and the complexity of information being learned.

1.4. Cognitive and personality factors in intentional learning

Cognition is not a unitary concept. Rather, it incorporates multiple domains including attention (focusing, shifting, dividing, or sustaining attention), memory (recall and recognition of information), language (production and reception), and executive function (planning, organizing thoughts, control, and inhibition), and visuomotor ability (visual search, drawing, and construction; Cumming et al., 2013). Classification of these cognitive abilities is not straightforward because cognitive processes from these putatively distinct domains must operate together to support behaviour. For example, learning a new word does not just require one to remember the association between the letters and their meaning. Rather, it requires the learner to attend to the word (attention), memorize that word (memory), have the capability to learn that word (language), use it when appropriate (executive function), and see the words and use your mouth to produce that word (visuomotor ability). In addition, personality traits are also closely related to intentional learning given they share some underlying neural basis.

1.4.1. Attention

Attention is our ability to choose and concentrate on certain stimuli given our goals. We could learn effectively in complex environments because we have the ability to employ selective attention to narrow down the dimensionality of a task (Jones & Canas, 2010; Niv et al., 2015; Wilson & Niv, 2012). Selective attention prioritizes some part of the environment for learning, therefore reducing the number of elements or stimulus configurations that the learner has to face

(Leong et al., 2017). Empirically, research has investigated the relationship between attention and learning, for instance, Wulf et al. (1998) have shown that motor learning performance could be enhanced by “external focus” (directing the learner’s attention towards the results of their movements) rather than “internal focus” (directing the learner’s attention towards the body movements that producing the results) directing the performer’s attention to the results of their movement (“ motor learning can be enhanced by directing performers’ attention to the effects of their movements (‘‘external focus’’), rather than to the body movements producing the effect (‘‘internal focus’’). Attentional factors have also been suggested to contribute to learning by strengthening the coupling of goals to actions (Wulf & Lewthwaite, 2016). Electrophysiological recordings have detected the neural signals for attention for learning in the ACC, which plays a broad role in learning (Bryden et al., 2011). Computational models have also been developed to demonstrate how attention plays a role in learning (Nosofsky, 1987).

1.4.2. Language

Language refers to the ability to express and receive thoughts in a structured system. Language is important for understanding task instructions but may not play a central role in learning. Initial studies of the relationship between learning and language were in the areas of neuropsychology. For example, Milner (1964, 1965), Luria (1973), and Luria et al. (1964) found that patients with damage to the LPFC were able to understand and remember instructions, but they failed to execute these instructions. This phenomenon is termed “goal neglect” (Duncan et al., 1996). With other instances, this may suggest that learning (at least IBL) does simply rely on language or on remembering instructions but may be dependent on other cognitive capacities (e.g., cognitive flexibility). Additional evidence comes from that the phenomenon of goal neglect correlates with fluid intelligence (Duncan et al., 2008), and fluid intelligence can be predicted by the activities in the MD network but not the language network (Woolgar et al., 2018).

Although language is not essential for learning, it may aid learning (e.g., IBL; Cole et al., 2013). This is due to the unique ability of humans to use language to specify task states, even though they are abstract. For example, the task "lifting the yellow object" can be rapidly specified linguistically but may require some trial-and-error in other forms of task learning (Cole et al., 2013). In another word, linguistic capabilities make tasks specified as either possible or practical for learning a new task (Cole, 2009).

1.4.3. Memory

Two major classes of memory are long-term and short-term (working) memory. Learning and memory are closely related. Short-term memory refers to the ability to keep a small amount of information in a short period of time whereas long-term memory is the ability to store far less limited information and maintain it in the longer term (Camina & Güell, 2017). Long-term memory can then be further classified as explicit (declarative) and implicit (non-declarative) memory. Explicit memory includes episodic and semantic memory whereas implicit memory includes procedural memory, associative memory, non-associative memory, and priming.

Memory closely relates to learning and is also sensitive to the types of learning. For example, it has been reported that learners' working memory capacity does not associate with the rate of implicit learning but does predict the rate of explicit learning (see Janacsek & Nemeth (2013) for a review), and that aged-related reduction in working memory capacity affect explicit but not implicit learning performance (Chauvel et al., 2012). In addition, it has been reported that the neural systems (particularly the prefrontal cortices) that are involved in working memory do not show strong activations in implicit learning tasks (Aizenstein et al., 2004; Galea et al., 2010; Willingham et al., 2002).

1.4.4. Executive function

Executive function consists of various mental processes that allow the flexible adjustments of thoughts and actions across domains, which allows one to adapt to new rules and guide the selections of task-relevant information as goal-directed behaviour in an environment that varies continuously (Miller & Cohen, 2001). Cognitive control has been closely related to learning. By definition, intentional learning is a goal-directed behaviour and requires a high degree of cognitive flexibility. As proposed by Hampshire et al. (2016), intentional forms of learning involve flexible cognitive systems that rapidly adapt to encode temporary programs to process non-automated tasks in a controlled manner. Compositional coding was introduced by Cole et al. (2013, 2017), which proposed a key flexible hub mechanism underlying the human ability to learn novel tasks rapidly, via the transformation and reuse of task elements across task contexts (Cole et al., 2011; Singley & Anderson, 1985). These mechanisms may depend on the simultaneous segregation and integration of relevant task information among brain regions (Sporns et al., 2000). From a computational perspective, a recent review also built a computational model linking the mechanisms of cognitive control and learning (Collins & Frank, 2013).

Inhibitory control, one of the core functions of executive control, is also relevant to learning. Inhibitory control requires one's ability to control attention, behaviour, thoughts, and emotion to override a strong internal predisposition or external influence, but instead to serve one’s goals (Diamond, 2013). Without inhibitory control ability, old habits, thoughts, actions, and stimuli in the environment will continue to compete with optimal behaviours that are less dominant and may even override our intended response. Thus, inhibitory control enables us to inhibit what is irrelevant to our goals and to choose how to behave rather than being unthinking creatures of habits (Diamond et al., 2013).

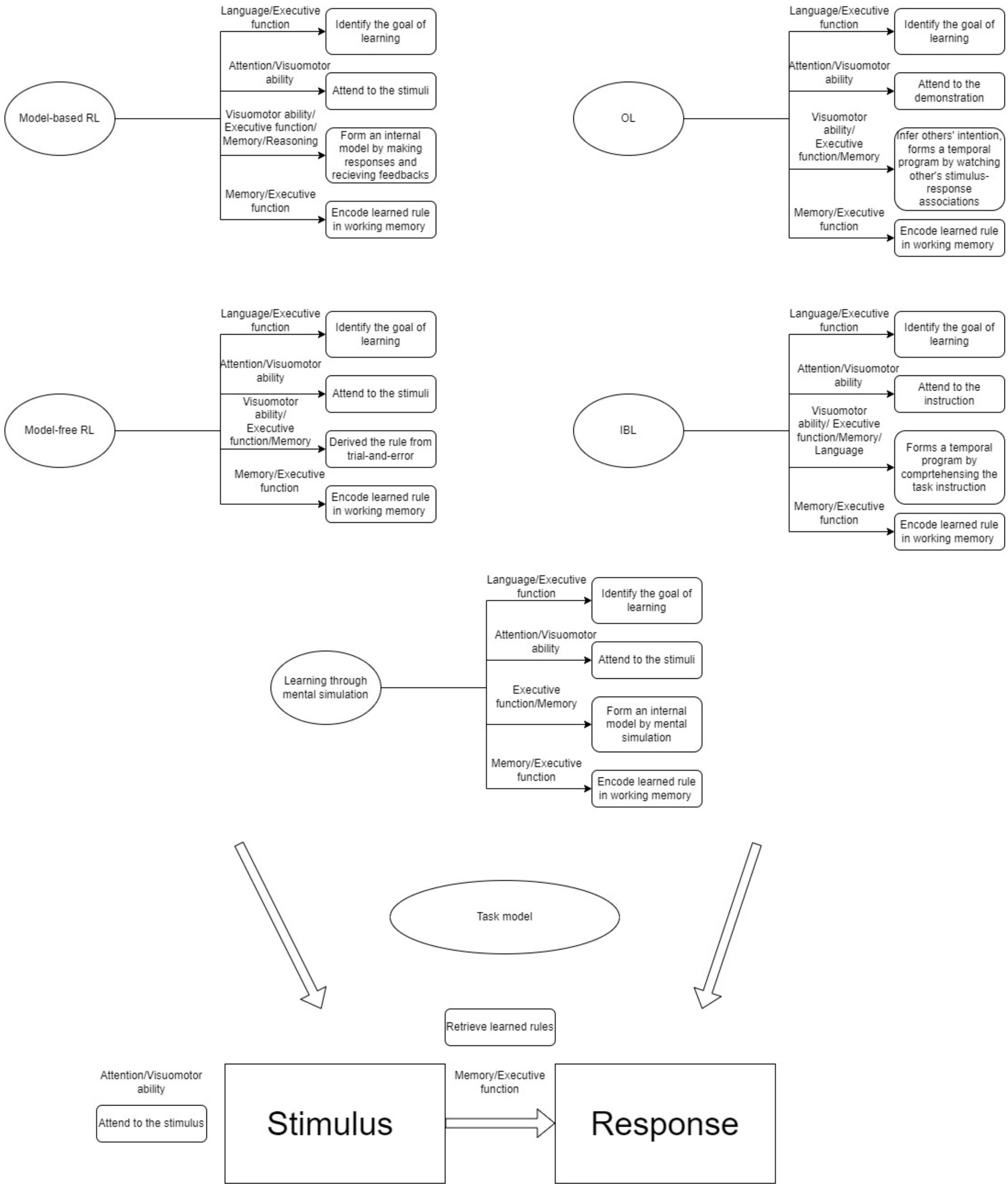
1.4.5. Reasoning

Reasoning is a thinking activity that has an important role in our lives. Thus, the ability to reason is crucial to all major theories of intelligence structure. The ability to reason is pivotal whenever "we think about the causes of events and actions, when we pursue discourse, when we evaluate assumptions and expectations based on our prior knowledge, and when we develop ideas and plans" (Wilhelm, 2005). Reasoning broadly refers to the ability to draw conclusions to inform problem-solving and decision-making. Given this, model-based RL may specifically require this ability as people have to learn by building an internal model for future inferences.

1.4.6. A cognitive model of learning

In the cognitive model I am proposing (Figure.4), in model-free RL, one first has to identify the goal of learning, which is typically conveyed in a linguistic format in a psychological testing setting, thus executive control (e.g., identifying the goal) and linguistic ability (e.g., understanding the instruction) are required. Then the learner focuses on stimuli that he/she is learning, thus attention and visuomotor ability are required. Next, the learner learns by making response and receiving feedbacks, which requires visuomotor ability (e.g., making a response and visually see stimuli and feedbacks), executive control (e.g., carrying out goal directed behaviours), and memory (e.g., remember what the previously encountered stimuli and outcomes associations are). Finally, through practice, the learner derives rules and encodes them in working memory, which requires memory and executive functions.

Figure.4. The sub-processes of intentional learning. This paradigm illustrates what sub-processes are for different types of intentional learning and what basic cognitive abilities are putatively required for these sub-processes.



In model-based RL, the learner first has to identify the goal of learning, which is typically conveyed in a linguistic format in a psychological testing setting, thus executive control (e.g., identifying the goal) and linguistic ability (e.g., understanding the instruction) are required. Then the learner focuses on stimuli that he/she is learning, thus attention and visuomotor ability are required. Next, the learner forms an internal model by making response and receiving feedbacks, which requires visuomotor ability (e.g., making a response and visually see stimuli and feedbacks), executive control (e.g., carrying out goal directed behaviours), memory (e.g., remember what the previously encountered stimuli and outcomes associations are), and reasoning (e.g., building the internal model to inform problem-solving and decision-making). Finally, through practice, the learner derives rules and encodes them in working memory, which requires memory and executive functions.

In OL, the learner first has to identify the goal of learning, which is typically conveyed in a linguistic format in a psychological testing setting, thus executive control (e.g., identifying the goal) and linguistic ability (e.g., understanding the instruction) are required. Then the learner focuses on stimuli that he/she is learning, thus attention and visuomotor ability are required. Next, the learner infers other's intention, and then form a temporal paradigm through watching other's S-R associations, which requires visuomotor ability (e.g., making a response and visually see stimuli and feedbacks), executive control (e.g., carrying out goal directed behaviours), and memory (e.g., remembering what the previously watched S-R-O associations are). Finally, through practice, the learner derived rules and encodes them in working memory, which requires memory and executive functions.

In IBL, the learner first has to identify the goal of learning, which is typically conveyed in a linguistic format in a psychological testing setting, thus executive control (e.g., identifying the goal) and linguistic ability (e.g., understanding the instruction) are required. Then the learner focuses on stimuli that he/she is learning, thus attention and visuomotor ability are required. Next, the learner learns from instructions, which requires language (e.g., comprehending the instructions), visuomotor ability (e.g., making a response and visually see stimuli and feedbacks), executive control (e.g., carrying out goal-directed behaviours), and memory (e.g., remembering what the previously encountered S-R associations are). Finally, through practice, the learner derived rules and encodes them in working memory, which requires memory and executive functions.

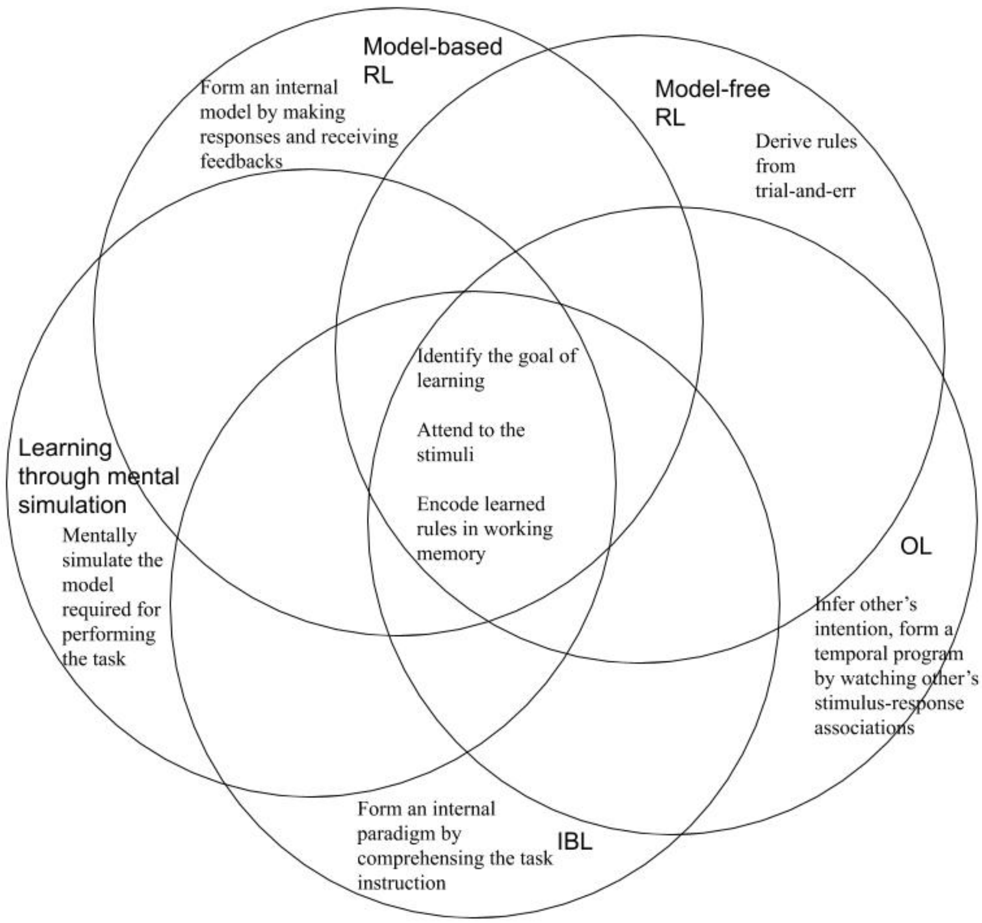
In learning from mental simulation, the learner first has to identify the goal of learning, which is typically conveyed in a linguistic format in a psychological testing setting, thus executive control (e.g., identifying the goal) and linguistic ability (e.g., understanding the instruction) are required. Then the learner focuses on stimuli that he/she is learning, thus attention and visuomotor ability are required. Next, the learner builds an internal model by simulating the scenarios where they encounter the stimuli and have to make appropriate responses, which requires executive control (e.g., carrying out goal-directed behaviours) and memory (e.g., remembering what the simulated S-R associations are). Then through practice, the learner reinforces learned rules and encodes them in working memory, which requires memory and executive functions.

All of the above-mentioned sub-processed in different types of intentional learning leads to a task model for subsequent implementation. In the implementation stage, the learner first must attend to the stimulus (requires attention and visuomotor ability), then retrieves learned rules from memory (requires memory and executive function), and finally makes a response (requires visuomotor ability).

1.4.6.1. Common and distinct sub-processes in different types of intentional learning

Thus, five types of intentional learning involve different combinations of the same underlying processes (Figure.5). Identifying the goal of learning, attending to the stimuli, encoding learned rules into working memory are shared characteristics of all types of intentional learning, but the way in which a learner acquires rules differs. Specifically, in model-free RL, a learner learns by making responses and receiving feedback without such an internal model, whereas in model-based RL, a learner learns by making responses and receiving feedback with an internal model. In OL, one has to infer another's intention and then forms a temporal program by integrating information from watching other's S-R associations whereas a learner forms a temporal program by comprehending the instruction in IBL. In learning from mental simulation, the learner has to simulate the scenario where they encounter the stimuli and make appropriate responses.

Figure.5. Common and distinct processes required in different types of intentional learning. This figure is made of five circles that represent each type of intentional. The processes in the very middle represent the common processes of all types of intentional learning whereas processes in the circles that represent each type of intentional learning indicate that these processes are distinct for that type of learning.



1.4.7. Role of personality in psychometrics of learning

Personality is closely associated with learning. However, past research has extensively focused on personality and learning from an educational psychology perspective, much less is known about personality relates to different types of intentional learning classified by its cognitive properties.

1.4.7.1. Early research in educational psychology

Early in 1978, Biggs proposed the 3P model that captures student learning after the Lewinian model which suggested that behaviour is a result of the interaction between the individual and the environment. Specifically, the first P in the model stands for “presage,” which consists of components including student characteristics and the learning environments. The second P in the model refers to interactions between the student's characteristics and the learning environment, which is the study process. In turn, the student’s study process affects the third P (i.e., product-the learning outcome). Personality is one of the major factors that is related to a student's characteristics (see Biggs, 1970; Biggs & Das, 1973).

The study process of the student has been investigated regarding their learning approaches to their learning tasks (Zhang, 2003). There are three learning approaches including surface (i.e., reproduction of what is being taught to meet the minimum requirement of learning), deep (i.e., a real understanding of what is being taught), and achieving (i.e., maximizing one’s grade). Zhang (2003) found that Conscientiousness, Extraversion, and Openness are positively associated with deep and achieving strategies but negatively associated with surface strategies. By contrast, Neuroticism was negatively associated with deep achieving strategies but positively related to surface strategy (Zhang, 2003). Agreeableness was only associated with negative surface strategy.

A latter study proposed four learning styles including synthesis-analysis (i.e., “processing information, forming categories, and organizing them into hierarchies”), elaboration (i.e., “connecting and applying new ideas to existing knowledge and to the learner’s personal experiences”), methodical study (i.e., “consists of what is traditionally emphasized in most academic environments, such as being careful and methodical while completing all assignments on time”) and factor retention (i.e., “involves processing information so that the main ideas are memorized with the goal of doing well on tests rather than understanding the meaning of what is being learned”; Komarraju et al., 2011). Komarraju et al. (2011) found that Conscientiousness and Agreeableness are positively associated with all four learning styles (i.e., synthesis analysis, methodical study, fact retention, and elaborative processing). However, Neuroticisms had negative associations with all these learning styles. Moreover, Openness and Extraversion were positively related to elaborative processing.

Thus, insights from earlier educational psychology research suggest that personality is associated with individual variability in learning approaches.

1.4.7.2. The associations between brain structures and personality

The Big Five is closely related to brain structure although there are some inconsistencies. One study has found that the Big Five personality traits are associated with the size of theoretically associated regions of the brain (see also DeYoung et al., 2009). Specifically, DeYoung et al. (2010) found that Neuroticism is associated with brain regions that are related to threat, punishment, and negative affect. Specifically, Neuroticism is negatively associated with dorsomedial PFC and in portions of the left medial temporal lobe, including posterior hippocampus, portions of basal ganglia and midbrain, including globus pallidus and bilateral subthalamic nuclei, and regions in the right precentral gyrus. In addition, brain regions that have associations with Neuroticism were found in bilaterally in mid-cingulate cortex, extending into the white matter of the cingulate gyrus and, in the left hemisphere, into the caudate as well as one region in the middle temporal gyrus and one in the cerebellum, Agreeableness is associated with the volume of brain regions that process information associated with others (e.g., the retrosplenial region of PCC, superior temporal sulcus, adjacent superior temporal gyrus, and fusiform gyrus). Conscientiousness is associated with volume of the lateral prefrontal cortex, which is a brain region that is associated with planning and controlling behaviour. Extraversion is associated with the volume of the medial orbitofrontal cortex, which is a brain region involved in reward information processing. However, no association between Openness and brain volume was found. Omura et al. (2015) found that Neuroticism is negatively related to the gray matter volume of the right amygdala whereas Extraversion is positively associated with the gray matter volume of the left amygdala. Another study also found a significant relationship between Neuroticism and gray matter volume of the left amygdala (Koelsch et al., 2013). Gardini et al. (2009) found that Novelty Seeking (a facet of Extraversion; e.g., De Fruyt et al., 2000) is positively related to grey matter volumes in the cingulate cortex. Harm Avoidance (a facet of Neuroticism; e.g., De Fruyt et al., 2000) is negatively related to those of the orbitofrontal, occipital, and parietal cortices. Additionally, Reward Dependence (a facet of Extraversion; e.g., De Fruyt et al., 2000) is associated with a decreased value in the caudate nucleus. To summarise, although there are associations between personality traits and brain regions, there seem to be inconsistent findings across studies.

1.4.7.3. The associations between compulsivity trait and learning

In addition to traditional personality models, more recent work has developed tool such as the Cambridge–Chicago Compulsivity Trait Scale (CHI-T) for measuring compulsivity (i.e., the tendency towards excessive and repetitive behavior inconsistent with one's goals, which may result in negative consequences). However, the associations between compulsivity trait and learning are far less understood although there is evidence regarding how diseases characterized with high compulsivity such as the obsessive-compulsive disorder (OCD) are related to learning and cognition in general. For instance, deficits in cognitive flexibility, memory, and goal-directed actions are found in adults with OCD (Abramovitch et al., 2013; Gillan et al., 2011;

Purcell et al., 1998). Impaired goal-directed control is a hallmark of adult OCD (Gillan et al., 2011). In addition, Gottwald et al. (2018) found that adolescents with OCD have widespread learning and memory impairments. These associations may be further explained by the underlying brain regions that are associated with both compulsivity and learning such as the ventral striatum and putamen (Tzagarakis, 2022).

1.4.7.4. The purpose and hypothesis of Chapter 4

Thus, the purpose of Chapter 4 is to use the short BFI, CHI-T, and cognitive tasks to investigate how personality traits relate to different types of intentional learning (i.e., instruction-based, observational, and reinforcement) at different levels of complexity (i.e., simple, complex, and model-based). I hypothesise that there are differential relationships between personality, cognitive performance, and intentional learning abilities.

Chapter 2

Validation of the Little Big Five Personality Inventory at Large Scale: Findings in the general population and in people with common mental and neurological disorders

2.1. Abstract

The five-factor model of personality (the Big Five) consists of a set of broad personality domains or domains consisting of Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness, which can be measured in a questionnaire that is typically measured 44 items. However, instruments with many items could be a source of measurement error, which makes it hard to be implemented in the clinical population and can also be unwieldly in cohort studies where a variety of scales are deployed in sequence. Conversely, the brief 5 and 10-item versions have poor reliability. Thus, the aim of the current study is to validate an 18-item version of the Big Five and evaluate the sensitivity of the resultant trait estimates to psychiatric and neurological conditions using data collected from a large-scale citizen science cohort. I found that the 18-item version of the Big Five had higher validity and test-rest reliability compared to other shortened versions. Like full-version of the Big Five, they are also associated with demographic characteristics. This instrument was more sensitive to psychiatric comparing to neurological conditions. Openness and Neuroticism tended to be higher whereas Conscientiousness tended to be lower in participants with psychiatric and neurological conditions. Extraversion and Neuroticism did not show a clear pattern. This study may imply that the 18-item version of the Big Five is a valid instrument to capture personality traits in people with psychiatric and neurological conditions.

2.2. Introduction

The five-factor model of personality (i.e., the Big Five) is a set of broad personality domains consisting of Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Goldberg, 1993). As opposed to being reserved and quiet, individuals who score high in Extraversion are assertive and sociable. Agreeable people are polite and cooperative, rather than rude and antagonistic. Individuals who score high in Conscientiousness are orderly and task-focused, rather than being disorganised and distractable. Neurotic people tend to experience negative emotions rather than being emotionally resilient. Finally, people who score high in Openness have broad interests, are sensitive to art and beauty, prefer novelty rather than having narrow interests, being indifferent to art and beauty, and preferring routine. It is agreed in the literature that the Big Five capture the most important basic individual differences in interpersonal functioning personality traits. Moreover, many other personality models could also be conceptualized in terms of the Big Five (Soto & Jackson, 2013).

Since the instruments for the Big Five personality assessments are extensive, often compromising more than 40 items, one of modern research objectives has been to develop shortened scales (e.g., Caprara, 1994; Gouveia et al., 2021; Laros et al., 2018; Rammstedt & John, 2007; Saucier, 2007). There is large amount of empirical evidence suggesting that instruments with many items could be a source of measurement error (Laros et al., 2018). For instance, long instruments could induce discouragement, fatigue, and inattention in the participants, especially making them hard to implement in clinical groups. Furthermore, a huge number of items may impede the joint administration of multiple instruments. Therefore, scales with fewer items that could potentially avoid the problems outlined are favored given they have acceptable reliability and validity (Laros et al., 2018). However, these shortened scales are not always validated at large scales with cross-validation which put them at risk of generalising poorly and providing unreliable estimates (Kruyen et al., 2013; Smith et al., 2000). Thus, there is a need for a short but rigorously validated personality inventory suitable for use in different contexts including via online platforms and applying to patients who may have too much cognitive burden if taking the original inventory.

Common psychiatric and neurological disorders are known to associate with personality traits. Four alternative models have been proposed to account for the empirically demonstrated associations between personality and psychopathology; the predisposition/vulnerability model, complication/scar model, pathoplasty/exacerbation model and the spectrum model (Krueger & Tackett, 2003; Nigg, 2006; Tackett, 2006; Whittle et al., 2006). The predisposition/vulnerability model suggests that particular traits confer a greater risk for the development of a psychological disorder (Krueger & Tackett, 2003; Tackett, 2006). Conversely, the complication/scar model proposes that the development of psychological disorders alters an individual's premorbid personality (Tackett, 2006; Whittle et al., 2006). According to the pathoplasty/exacerbation model, the etiology of psychological disorders is independent of traits, however, premorbid temperament traits are purported to influence the manifestation, severity, and course of mental illness (Tackett, 2006; Whittle et al., 2006). The spectrum model conceptualises a dimensional relationship between temperament (i.e., a subset of personality)/personality and psychopathology, such that psychological disorders represent extreme poles of the continuum of individual differences in temperament (Krueger & Tackett, 2003; Nigg, 2006; Tackett, 2006).

However, few studies have investigated the relationship between them, especially between neurological conditions and personality. In a meta-analysis (N=117,899), Hakulinen et al. (2015) found that low Extraversion, high Neuroticism, and low Conscientiousness are associated with depressive symptoms. Similar conclusions were drawn from longitudinal analyses adjusted for baseline depressive symptoms, which indicated that low Extraversion, high Neuroticism, and low Conscientiousness are associated with an increased risk of depression at follow-up. In sum, depressive symptoms were associated with personality changes in Extraversion, Neuroticism, and Conscientiousness. Compared to depression, other psychiatric conditions are far less studied. There is limited evidence showing that Neuroticism decreases, and Extraversion increases when anxiety symptoms ameliorate in patients with panic disorder and agoraphobia (Reich et al., 1986). In a recent study, Karsten et al. (2012) found that only Neuroticism increases during an anxiety episode but not other personality traits.

Some studies have also looked at the relationships between ADHD symptoms and personality traits (e.g., Perroud et al., 2016). Based on the Temperament and Character Inventory (TCI), Perroud et al. (2016) found that Novelty Seeking (a facet of Extraversion; e.g., De Fruyt et al., 2000), Harm Avoidance (a facet of Neuroticism; e.g., De Fruyt et al., 2000), Self-Transcendence (a facet of Openness; e.g., De Fruyt et al., 2000), Self-Directedness (a facet of Neuroticism; e.g., De Fruyt et al., 2000), and Cooperativeness (a facet of Agreeableness; e.g., De Fruyt et al., 2000) were related to ADHD. In addition, Self-Directedness was the strongest personality trait associated with ADHD, which had a negative relationship with ADHD. As for OCD patients, one study has found a positive relationship between Neuroticism and the Maudsley Obsessive-Compulsive Inventory (MOCI) and negative associations between Openness, Agreeableness, and Conscientiousness and the MOCI (Fardin et al., 2017). There seemed to be inconsistent findings regarding personality and bipolar disorder. Some found that bipolar patients have increased Neuroticism compared to controls (Barnett et al., 2011; Jylhä et al., 2010; Nowakowska et al., 2005; Sparding et al., 2017), one found lower scores on

Agreeableness (Barnett et al., 2011) and higher Aggressiveness (Sparding et al., 2017) in bipolar patients, one found high disinhibition in patients with bipolar disorder (Sparding et al., 2017), and a few others found lower scores on Extraversion in bipolar patients (Barnett et al., 2011; Jylhä et al., 2010).

As for personality and neurological conditions, one study compared personality traits in patients with multiple sclerosis and healthy controls and found that multiple sclerosis patients have higher scores in Neuroticism and lower scores in Conscientiousness compared to controls (Abedini et al., 2012). Regarding personality and stroke, one recent systematic review found high rates of increased Neuroticism and decreased Extraversion in patients with stroke relative to normative data (Dwan & Ownsworth, 2019). One meta-analysis reported that Parkinson's patients had higher harm avoidance scores, and lower novelty-seeking scores compared to healthy controls. In addition, they had higher levels of Neuroticism, but lower levels of Openness and Extraversion associated with Parkinson's disease (Santangelo et al., 2018). However, to the best of my knowledge, none of the studies has looked at the relationship between personality and neurological conditions such as learning disability or traumatic brain injury (TBI).

Thus, the relationship between personality and psychiatric conditions and neurological conditions remains generally unclear with different results depending on the nature of the study (e.g., whether they are cross-sectional or longitudinal, whether they rely on self-report or not, and the sample size), which may not be robust due to these factors. The aim of this study is to determine the validity of the shortened Big Five Inventory (BFI) using large-scale datasets and apply the shortened personality inventory to patients with various psychiatric and neurological conditions to fill the gap in the literature. Based on the existing literature, I expect that my shortened Big Five is valid and a better alternative to both the full-scale Big Five and other shortened versions due to its reliability. Furthermore, I hypothesise that different personality traits will differentially associate with common psychiatric and neurological conditions, but the main trends are that Openness, Extraversion, and Neuroticism are positively affected whereas Agreeableness and Conscientiousness are negatively affected. Moreover, psychiatric conditions will be more closely related to personality compared to neurological conditions because there are more past findings reported associations between personality traits and psychiatric conditions comparing to associations between personality traits and neurological conditions.

2.3. Methods

2.3.1. Participants

All data were selected from participants who participated in the online GBIT Great British Intelligence Test (GBIT) study, which is an ongoing collaborative citizen science project with BBC2 Horizon.

Dataset 1: Dataset 1 (N=59,797) was collected from January through April 2020, this dataset contains the full version of the Big Five (44 items).

Dataset 2: Dataset 2 (N=21,177) was collected in May 2020, this dataset contains only the 18-item version of the Big Five. The selection of these 18 questions was based on their having heavy loadings onto the components based on Dataset 1. Participants completed the 18-item version of the Big Five again from December 2020 to January 2021.

Dataset 3: Dataset 3 was collected between December 2020-January 2021. Participants who are younger than 16 or older than 99 and who have any missing fields were removed which resulted in an N=87,983 for further analysis with a mean age of 46.58$\pm$15.84, 55.37% female, and 94.4% Caucasians. Among them, there were 4,854 participants indicated that they have depression but do not have anxiety, 4,682 participants indicated that they have anxiety but do not have depression, 6,047 participants indicated that they have both depression and anxiety, 368 participants indicated that they have ADHD, 476 participants indicated that they have OCD, 453 participants indicated that they have bipolar disorder, 2,305 participants indicated that they have other psychiatric conditions. As for the neurological patient groups, 978 participants indicated that they have a learning disability, 298 participants indicated that they have multiple sclerosis, 495 participants indicated that they have a stroke, 159 participants indicated that they have Parkinson's disease, 124 participants indicated that they have a traumatic brain injury, and 2603 participants indicated that they have other neurological conditions.

2.3.2. Materials

Participants were asked to complete a series of cognitive tasks and questionnaires online in the GBIT (Great Britain Intelligence Test) study. We extracted variables that are most relevant to this including age, handedness, gender, language, ethnicity, country of residence, education, occupation, psychiatric conditions, neurological conditions and the 44-item version and the "little" BFI, which consists of 18 items (see supplementary material).

2.3.3. Data analysis

2.3.3.1. Validation

In order to validate the Little Big Five, I used Dataset 1 using the full-scale Big Five Personality Inventory collected from GBIT. Data were randomly split into two halves. Then a exploratory factor analysis (EFA) with 5 oblique components was performed on these two data sets respectively. I then divided the raw score of the full-scale Big Five by the loading matrix. However, for the second half, I only divided the raw score of the "little" Big Five by the loading matrix generated by the first 18 columns from the loading matrix generated from the first half. This step ensured that factor scores are derived from the same factor model. I correlated scores from these two divisions. I repeated the same process for the 10-item version of the Big Five proposed by Rammstedt et al. (2007), and a 5-item version selected based on the heaviest loading question for each factor (i.e., personality trait). All analyses were performed on MATLAB 2018a.

2.3.3.2. Test-retest reliability

To confirm the consistency across two-time points, Dataset 2 in addition to Dataset 1 was used from GBIT. EFAs were performed on Dataset 1 and Dataset 2 respectively. Examination of the rotated component loading matrix produced the expected easily interpretable solution. Specifically, the components were labeled as Openness, Extraversion, Neuroticism, Agreeableness, and Conscientiousness as in the Big Five. I then correlated these scores for each personality trait from Dataset 1 with that from Dataset 2 to check the test-retest reliability. All analyses were performed on MATLAB 2018a.

2.3.3.3. Linear models

In order to analyze how the Big Five personality traits are affected by psychiatric and neurological conditions, I adapted a predictive normative modelling approach on Dataset 3: (1) the standardized component scores (mean=0, SD=1) from all participants were taken into a general linear model with demographic variables including age, gender, handedness, language, ethnicity, country, education, occupation, and income as predictors. (2) Demographic data from participants who had various psychiatric and neurological conditions were taken into the model respectively to predict scores based on their demographics. (3) The predicted scores were subtracted from the actual scores in patients, which results in deviation from expected scores, which are scores showing how far in standard deviation units each individual deviated from the score we would expect for someone who demographically was matched along all dimensions of the normative model.

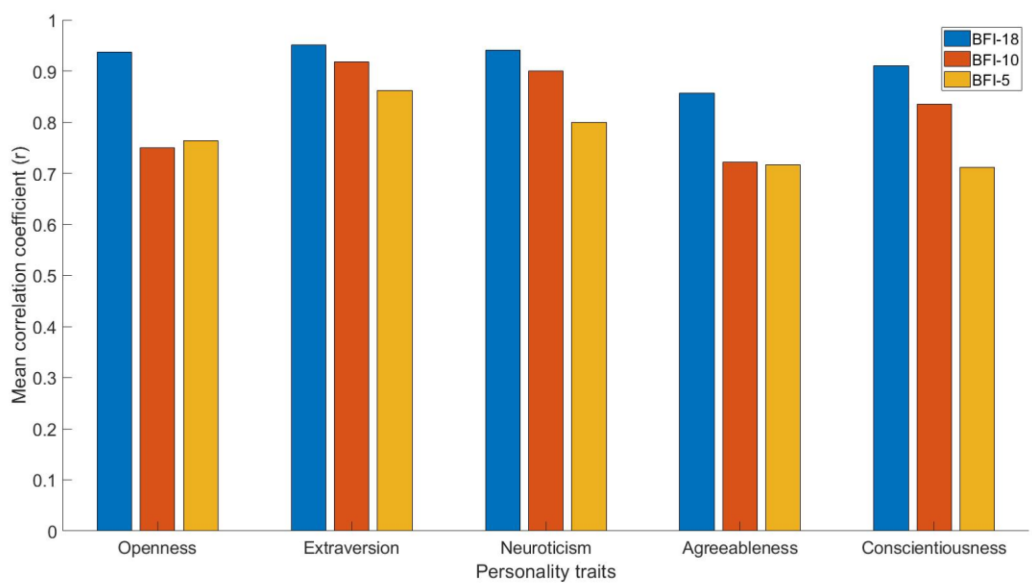
A one-sample t-test was performed to compare the differences in the standardised five component scores against zero. This approach is more advantageous than paired sample t-tests and analysis of variance (ANOVA) because it can control for confounders such as demographic information and does not require an equal sample size for each group. All analyses were performed on MATLAB 2018a.

2.4. Results

2.4.1. Validation

I found strong correlations between scores from the full-scale Big Five and the Little Big Five calculated using the same loading matrix on Openness ($r(29,896)=0.95$, $p<0.001$), Extraversion ($r(29,896)=0.94$, $p<0.001$), Neuroticism ($r(29,896)=0.91$, $p<0.001$), Agreeableness ($r(29,896)=0.94$, $p<0.001$), Conscientiousness ($r(29,896)=0.86$, $p<0.001$). However, the correlations between scores from the full-scale Big Five and the 10-item version were much lower Openness (r(29,896)=0.92, p<0.001), Extraversion (r(29,896)=0.90, p<0.001), Neuroticism (r(29,896)=0.84, p<0.001), Agreeableness (r(29,896)=0.75, p<0.001), Conscientiousness (r(29,896)=0.72, p<0.001). Similarly, the correlations between scores from the full-scale Big Five and the 5-item version are much lower for Openness (r(29,896)=0.86, p<0.001), Extraversion (r(29,896)=0.80, p<0.001), Neuroticism (r(29,896)=0.71, p<0.001), Agreeableness (r(29,896)=0.76, p<0.001), Conscientiousness (r(29,896)=0.72, p<0.001). Results were plotted in Figure.6.

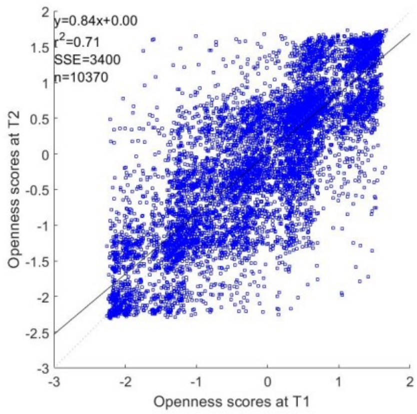
Figure.6. The correlation coefficients between scores from the full-scale Big Five and the little Big Five. These scores were calculated using the same loading matrix on each dimension of the Big Five Personality Inventory. Y axes=mean correlation coefficient (r).

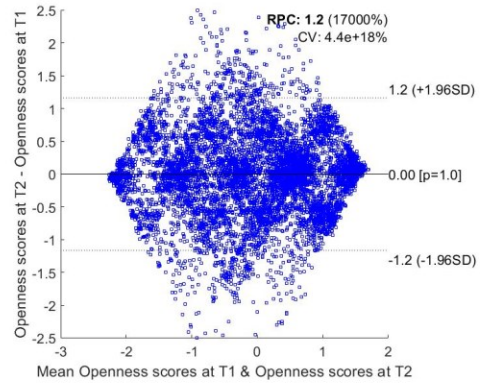


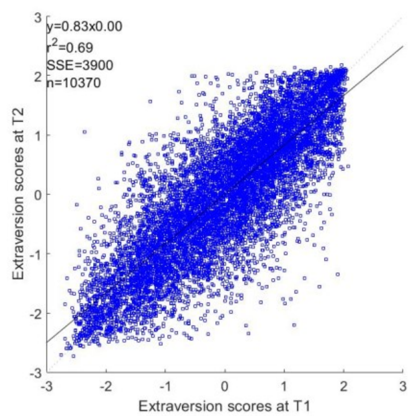
2.4.2. Test-retest reliability

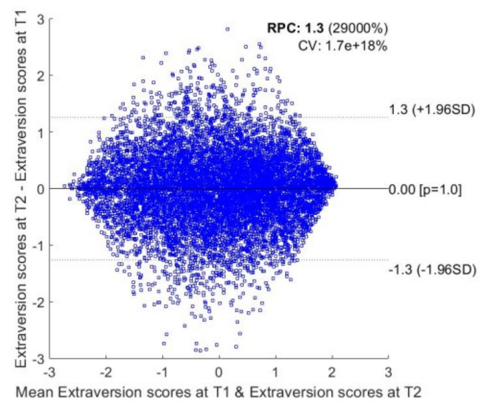
There were also strong positive correlations between components scores at Time 1 and Time 2 on Openness ($r(10,370)=0.84$, $p<0.001$), Extraversion ($r(10,370)=0.83$, $p<0.001$), Neuroticism ($r(10,370)=0.81$, $p<0.001$), Agreeableness ($r(10,370)=0.81$, $p<0.001$), Conscientiousness ($r(10,370)=0.73$, $p<0.001$). I also visualized our findings using correlation scatter plots and Bland–Altman plots (Figure.7; Altman and Bland, 1983).

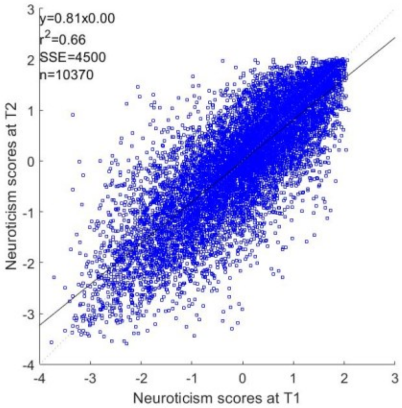
Figure.7. Correlation scatter plots and Bland–Altman plots of personality traits including Openness, Extraversion, Neuroticism, Agreeableness, and Conscientiousness scores at Time 1 and Time 2. Left panel: R^2=Pearson r-value squared, SSE=sum of squared error, and n=number of data points used. Right panel: RPC=reproducibility coefficient (1.96*SD), CV=coefficient of variation (SD of mean values in %).

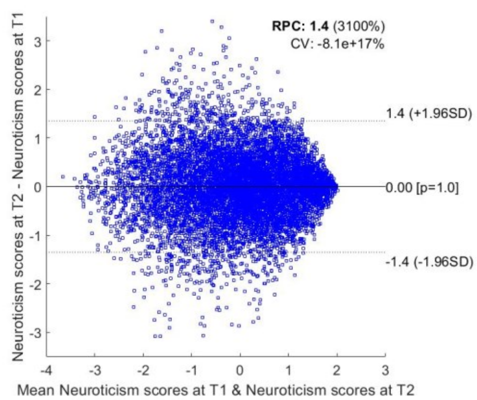

y=0.84x+0.00
r2=0.71
SSE=3400
n=10370
Openness scores at T2
Openness scores at T1

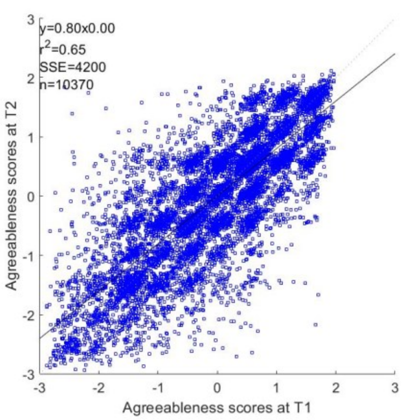

RPC: 1.2 (17000%)
CV: 4.4e+18%
1.2 (+1.96SD)
0.00 [p=1.0]
-1.2 (-1.96SD)
Openness scores at T2 - Openness scores at T1
Mean Openness scores at T1 & Openness scores at T2

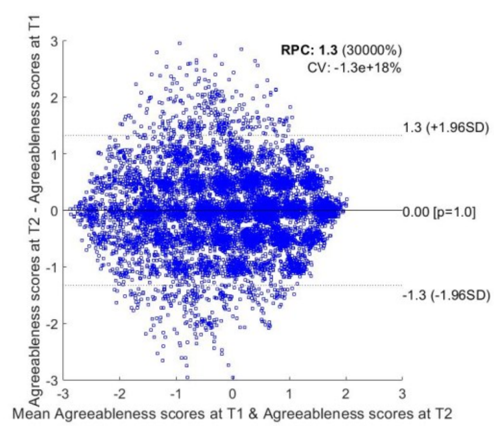

y=0.83x0.00
r2=0.69
SSE=3900
n=10370
Extraversion scores at T2
Extraversion scores at T1

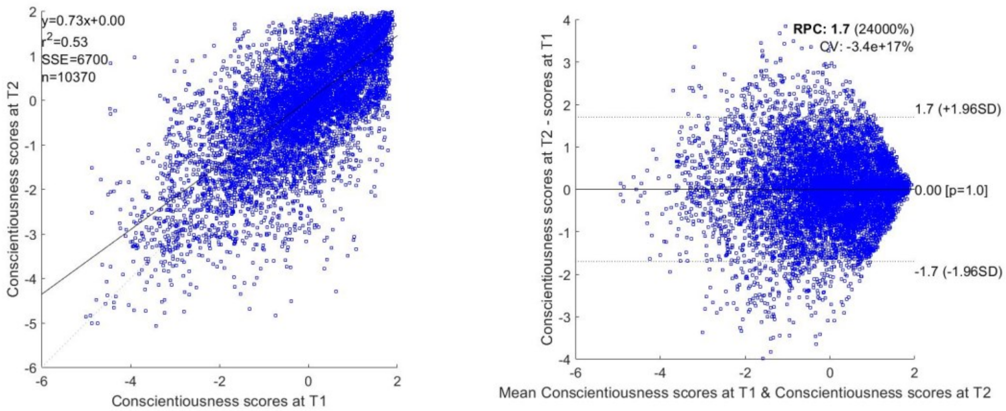

RPC: 1.3 (29000%)
CV: 1.7e+18%
1.3 (+1.96SD)
0.00 [p=1.0]
-1.3 (-1.96SD)
Extraversion scores at T2 - Extraversion scores at T1
Mean Extraversion scores at T1 & Extraversion scores at T2


y=0.81x0.00
r2=0.66
SSE=4500
n=10370
Neuroticism scores at T2
Neuroticism scores at T1


RPC: 1.4 (3100%)
CV: -8.1e+17%
1.4 (+1.96SD)
0.00 [p=1.0]
-1.4 (-1.96SD)
Neuroticism scores at T2 - Neuroticism scores at T1
Mean Neuroticism scores at T1 & Neuroticism scores at T2


y=0.80x0.00
r2=0.65
SSE=4200
n=10370
Agreeableness scores at T2
Agreeableness scores at T1

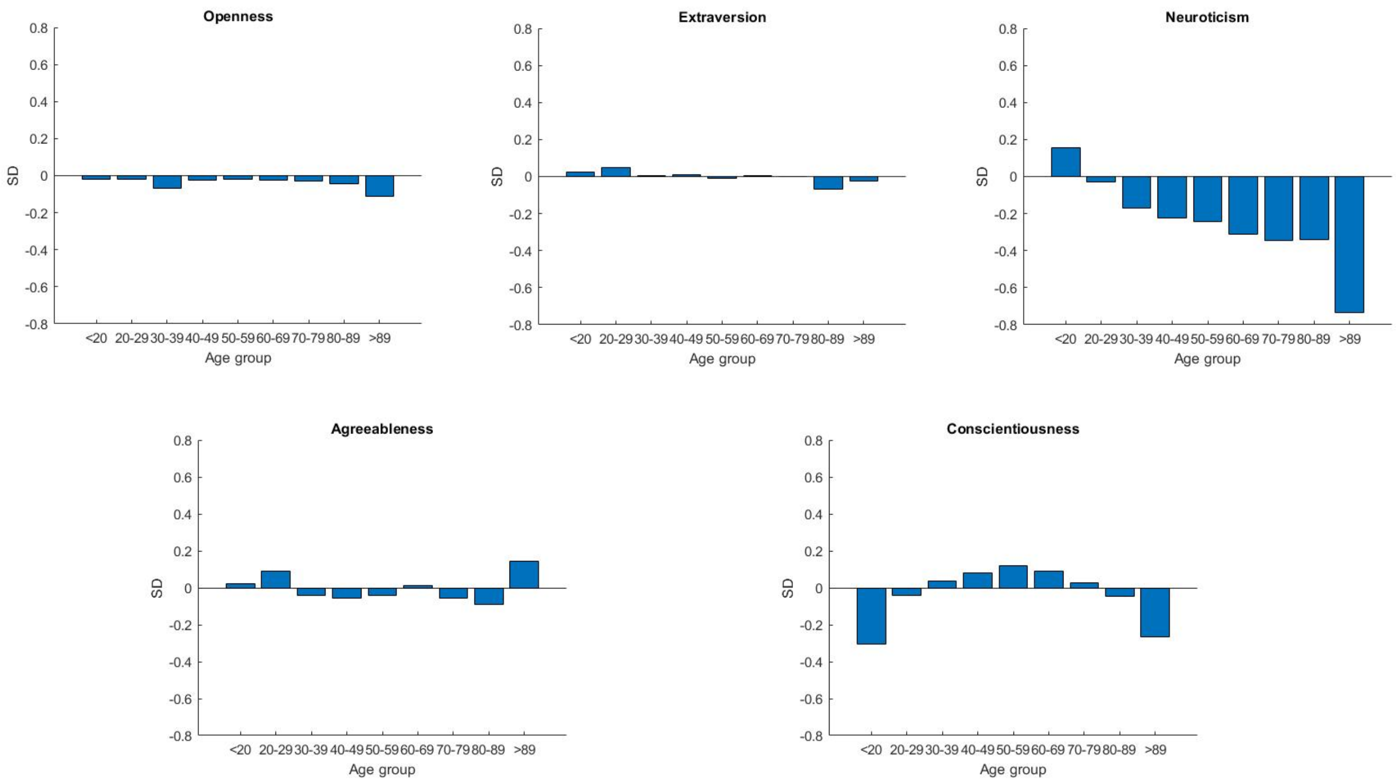

RPC: 1.3 (30000%)
CV: -1.3e+18%
1.3 (+1.96SD)
0.00 [p=1.0]
-1.3 (-1.96SD)
Agreeableness scores at T2 - Agreeableness scores at T1
Mean Agreeableness scores at T1 & Agreeableness scores at T2



2.4.3. The effects of demographics on personality

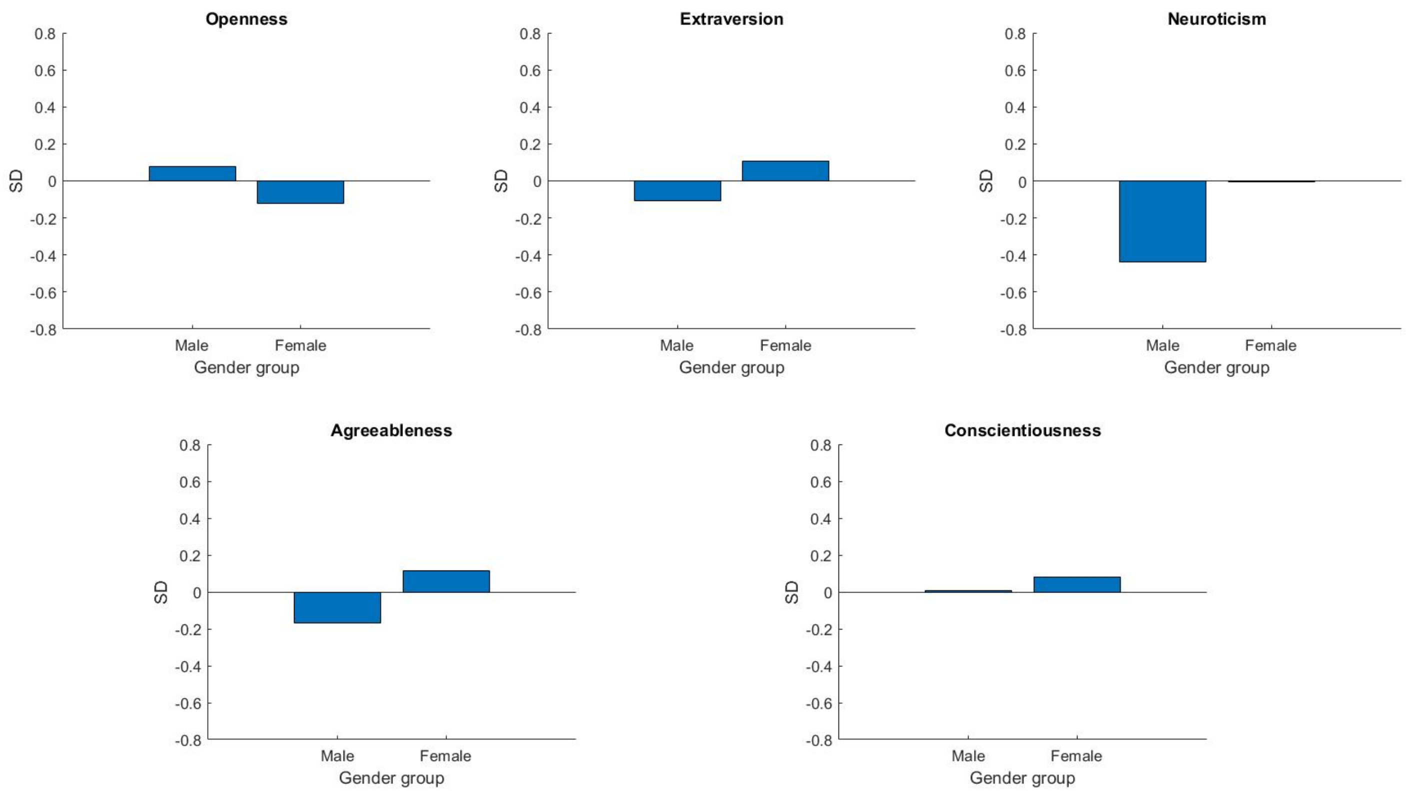
I found a significant main effect of age on all personality traits including Openness ($F(1, 69{,}244)=171.42$, $p<0.001$), Extraversion ($F(1, 69{,}244)=22.37$, $p<0.001$), Neuroticism ($F(1, 69{,}244)=299.02$, $p<0.001$), Agreeableness ($F(1, 69{,}244)=7.82$, $p<0.01$), Conscientiousness ($F(1, 69{,}244)=33.41$, $p<0.001$). Plotting them as a function of decade revealed that Neuroticism decreases with age, Conscientiousness has a inversed U-shaped function whereas Openness, Extraversion, and Agreeableness do not a have clear pattern (Figure.8).

Figure.8. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness as a function of age. There are associations between age and all dimensions of personality traits but the association between age and Openness, Extraversion, and Agreeableness did not show a clear pattern. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



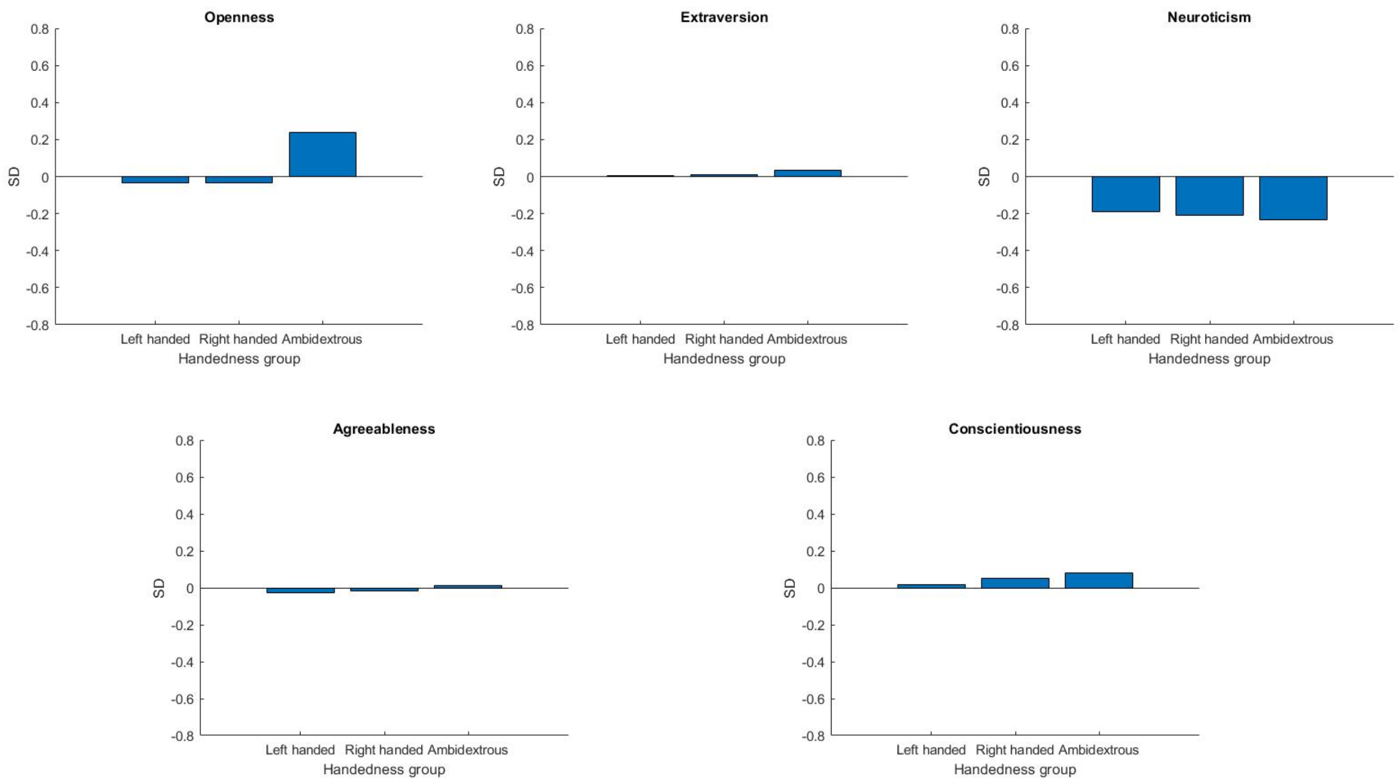
Similarly, gender had a main effect on Openness (($F(2, 69{,}244)=344.21$, $p<0.001$), Extraversion ($F(2, 69{,}244)=593.14$, $p<0.001$), Neuroticism ($F(2, 69{,}244)=512.85$, $p<0.001$), Agreeableness ($F(2, 69{,}244)=512.85$, $p<0.001$), Conscientiousness ($F(2, 69{,}244)=111.01$, $p<0.001$). Specifically, males had higher Openness scores than females (Cohen's $d=0.20$) whereas females had higher Extraversion (Cohen's $d=0.22$), Neuroticism (Cohen's $d=0.43$), Agreeableness (Cohen's $d=0.28$), and Conscientiousness (Cohen's $d=0.07$) scores than males (Figure.9).

Figure.9. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in males and females respectively. There are associations between gender and all dimensions of personality traits with males having significant higher scores in Openness but lower scores in Extraversion, Neuroticism, Agreeableness, and Conscientiousness in females. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



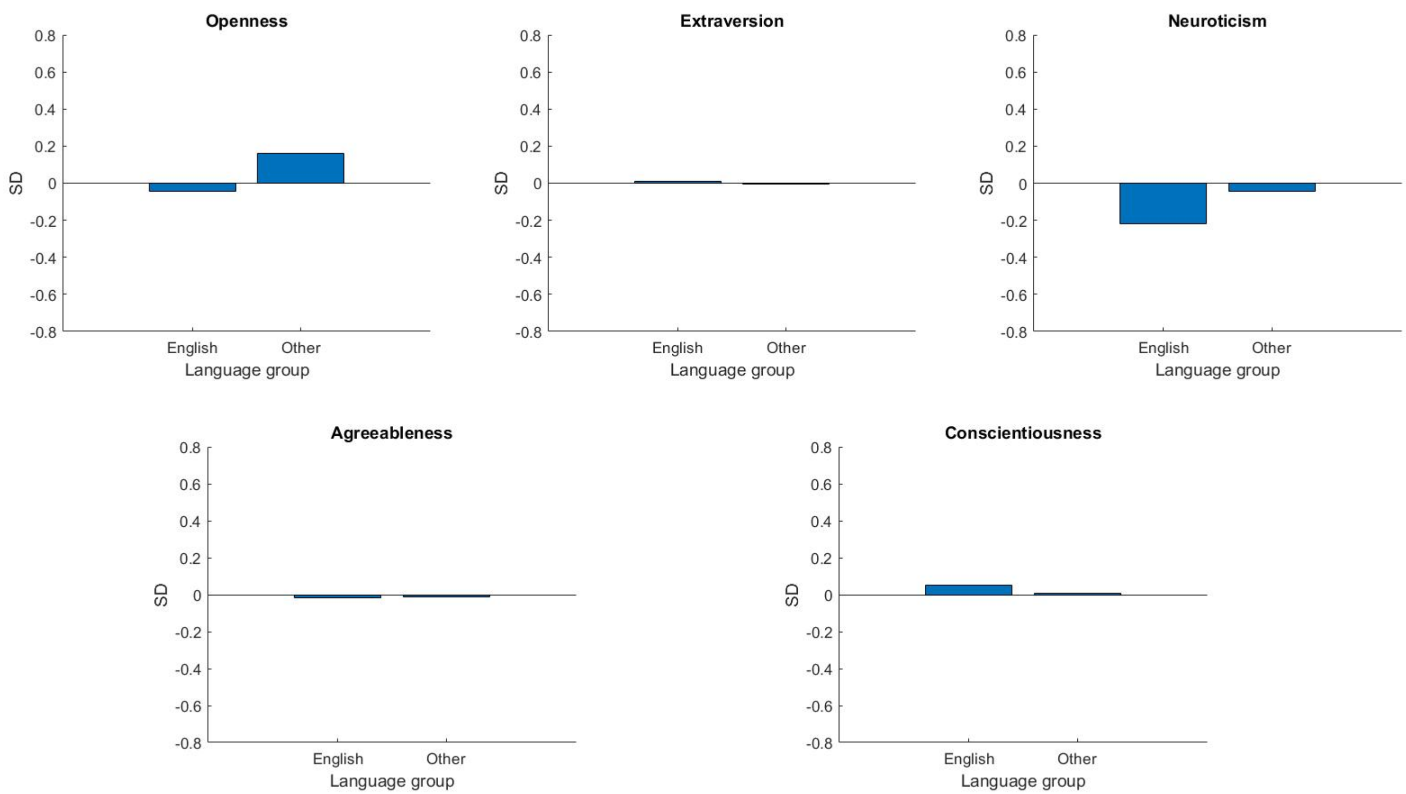
In addition, handedness had a significant effect on Openness ($F(2, 69{,}244)=57.72$, $p<0.001$), Neuroticism ($F(2, 69{,}244)=4.45$, $p=0.01$), and Conscientiousness ($F(2, 69{,}244)=4.12$, $p<0.05$) but not Extraversion nor Agreeableness. Specifically, the ambidextrous had higher Openness scores than the left-handed (Cohen's $d=0.28$) and the right-handed (Cohen's $d=0.28$) whereas the differences in Neuroticism and Conscientiousness were neglectable with a general trend that the right-handed score higher than the left-handed and ambisextrous score higher than the right-handed (Figure.10).

Figure.10. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in the left-handed, right-handed, and ambidextrous respectively. There are associations between handedness and Openness, and Conscientiousness but not Extraversion nor Agreeableness. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



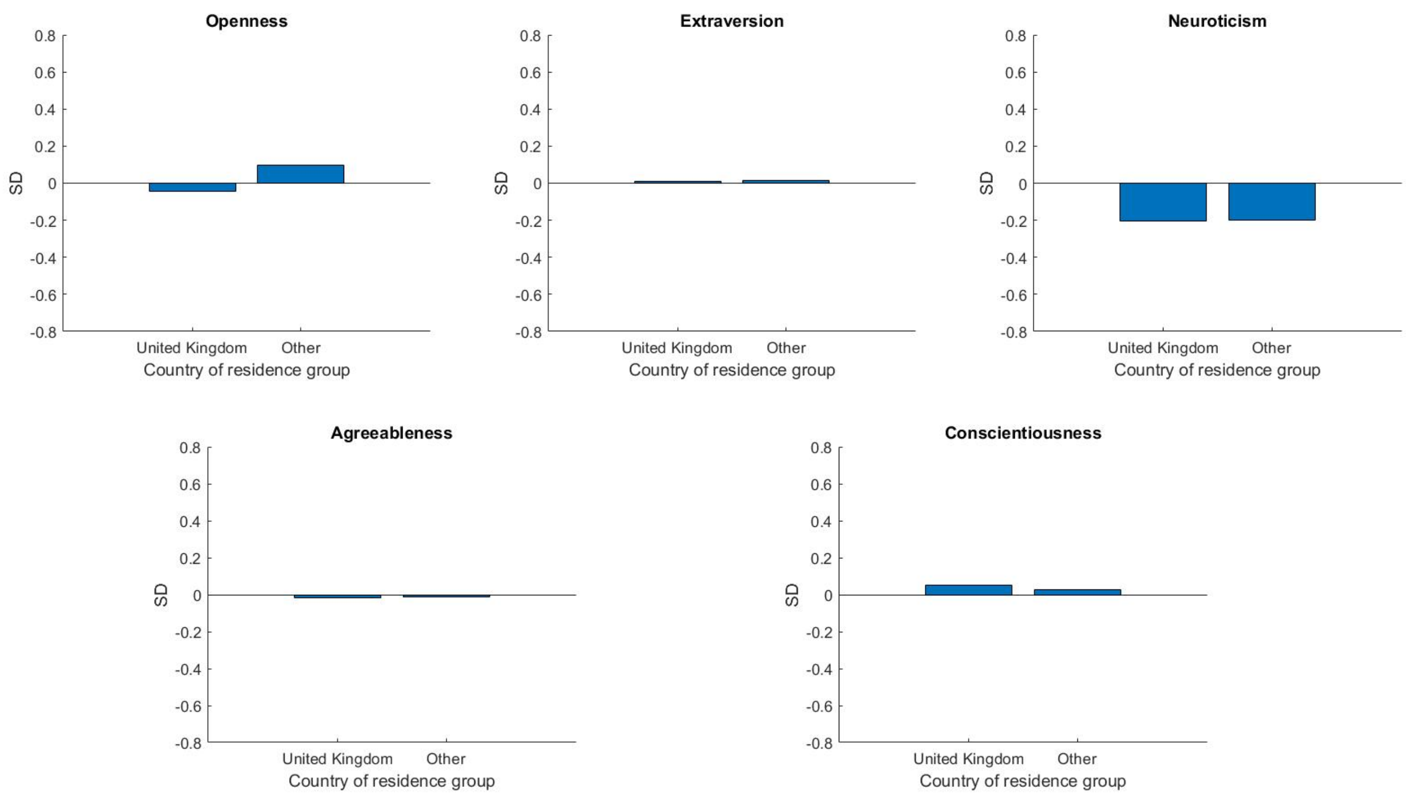
There was also a significant effect of language on Openness ($F(1, 69,244)=82.77$, $p<0.001$), Neuroticism ($F(1, 69,244)=56.69$, $p<0.001$), Agreeableness ($F(2, 69,244)=10.83$, $p<0.001$), but not Extraversion nor Conscientiousness. Specifically, other language speakers had significant higher Openness (Cohen's d=0.20) and Neuroticism (Cohen's d=0.17) scores whereas the difference in Agreeableness score between English speaker and other language speakers was neglectable (Figure.11).

Figure.11. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in the English and other language speaking participants respectively. There are associations between language and Openness, Neuroticism, and Agreeableness but not Extraversion nor Conscientiousness. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



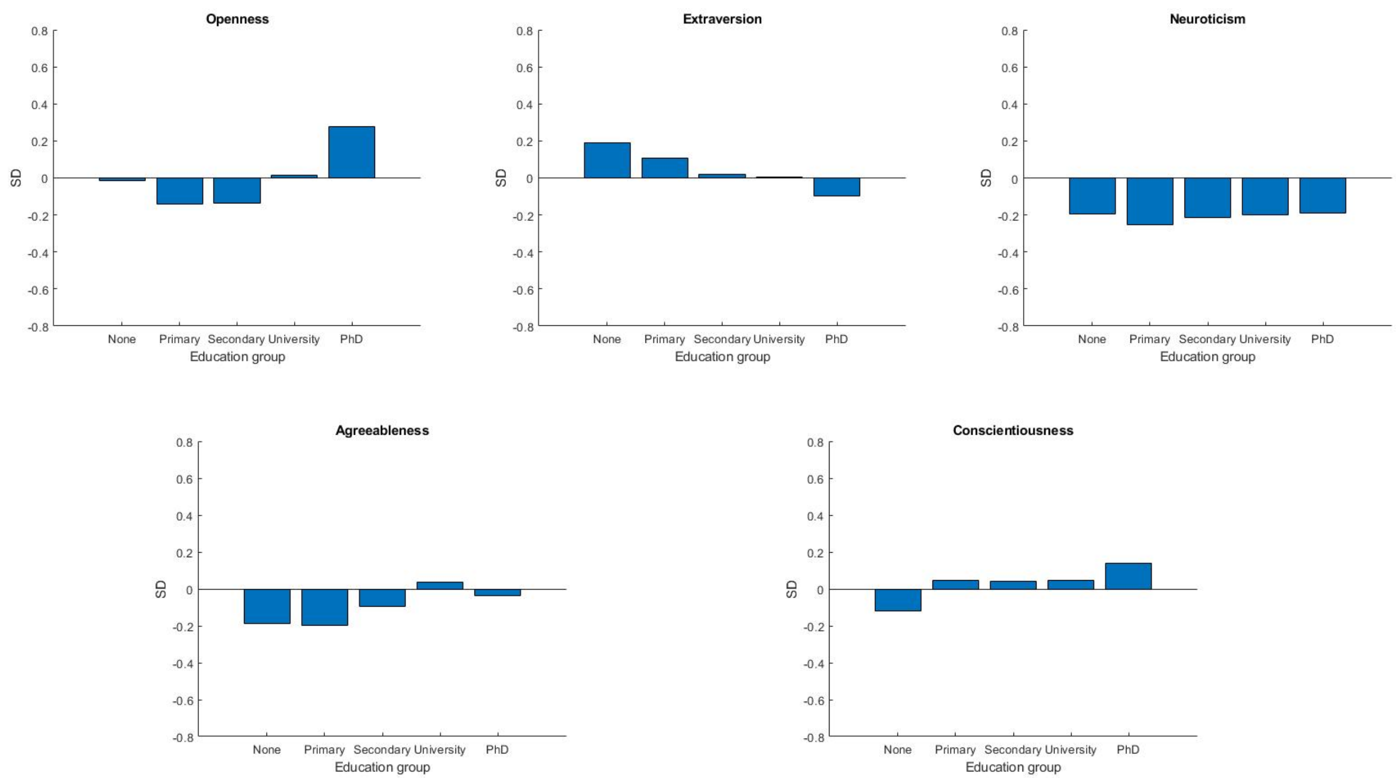
I also found a significant effect of country of residence on Openness ($F(1, 69{,}244)=46.58$, $p<0.001$) and Conscientiousness ($F(1, 69{,}244)=4.24$, $p<0.05$) but not on Extraversion, Neuroticism, and Agreeableness. Specifically, people from other countries had a significant higher score in Openness compared to people from the United Kingdom (Cohen's d=0.14). However, the difference in Conscientiousness score in people from the United Kingdom and people from other countries was neglectable (Figure.12).

Figure.12. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in participants from the United Kingdom and other countries respectively. There was a significant effect of country of residence on Openness and Conscientiousness but not on Extraversion, Neuroticism, and Agreeableness. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



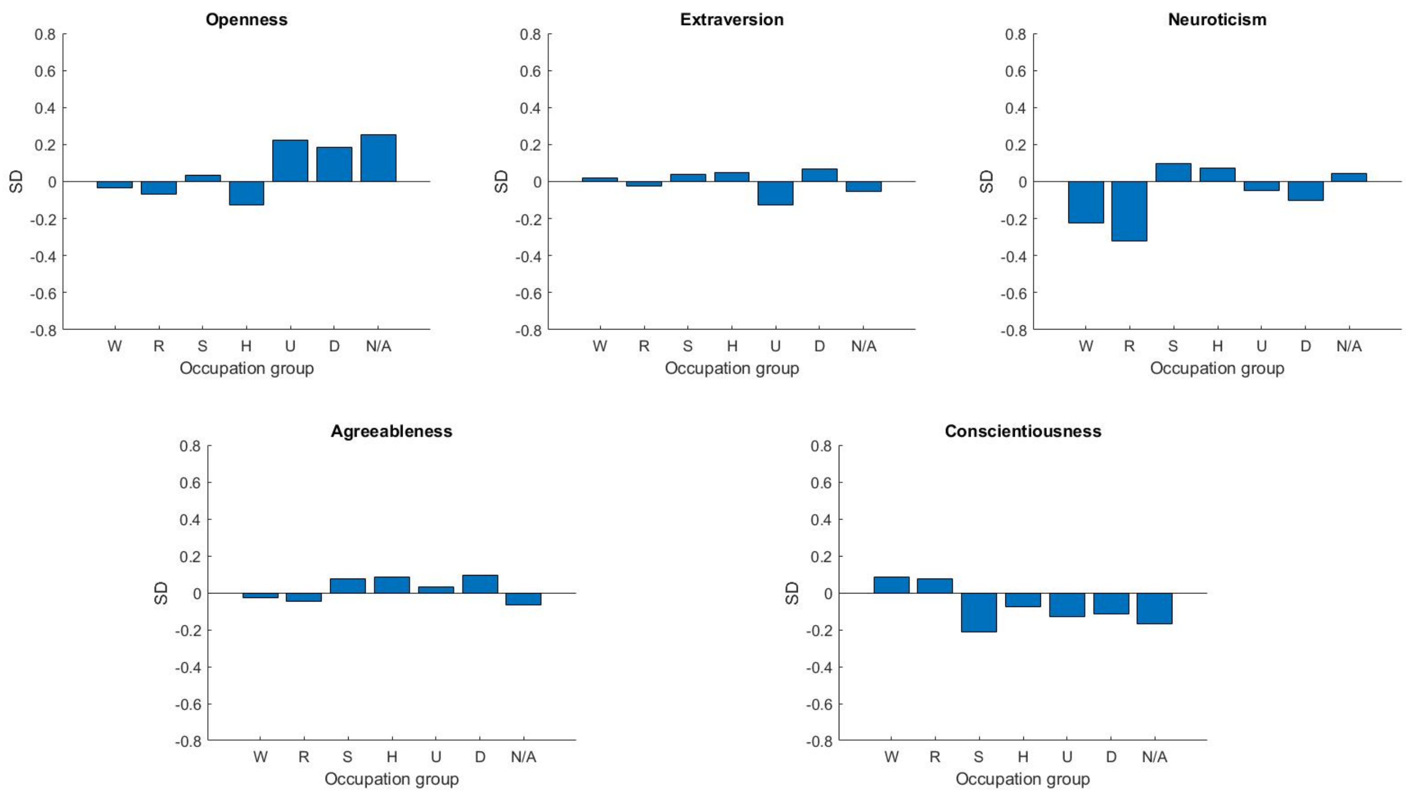
Education had a significant main effect on Openness ($F(4, 69{,}244)=175.58$, $p<0.001$), Extraversion ($F(4, 69{,}244)=34.33$, $p<0.001$), Neuroticism ($F(4, 69{,}244)=9.78$, $p<0.001$), Agreeableness ($F(4, 69{,}244)=105.19$, $p<0.001$), and Conscientiousness ($F(4, 69{,}244)=8.02$, $p<0.001$). Specifically, people with a PhD had the highest Openness and Conscientiousness scores and the lowest Extraversion score whereas people with a university degree had the highest Agreeableness score. However, Neuroticism score was similar in people with various education levels (Figure.13).

Figure.13. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in participants who received no, primary, secondary, university, and PhD education respectively. Education is associated with all personality traits with people with PhD generally having higher Openness, Conscientiousness, and Agreeableness scores but a lower Extraversion score. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



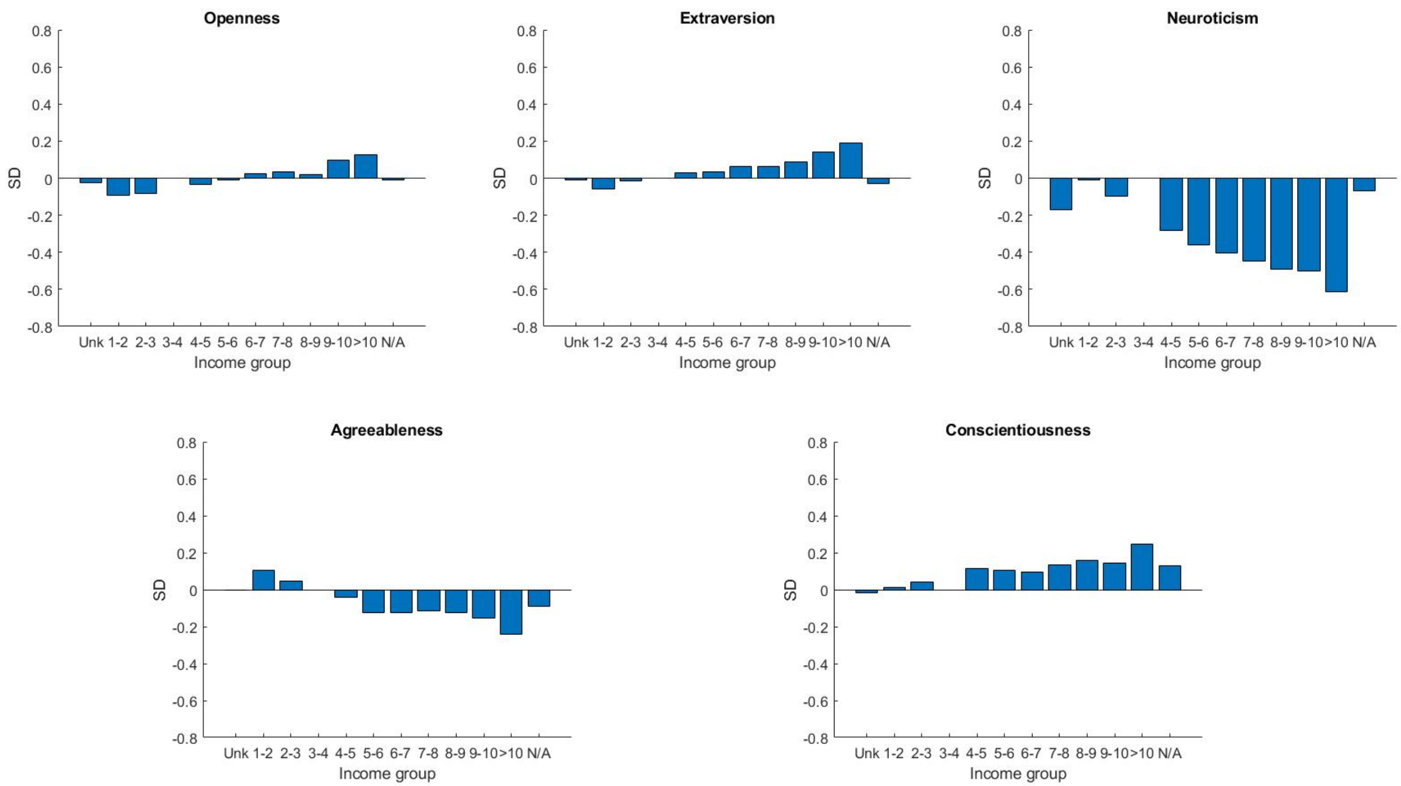
Results also revealed that there is a significant main effect of occupation on Openness ($F(5, 69{,}244)=59.95$, $p<0.001$), Extraversion ($F(5, 69{,}244)=3.22$, $p<0.01$), Neuroticism ($F(5, 69{,}244)=22.12$, $p<0.001$), and Conscientiousness ($F(5, 69{,}244)=18.40$, $p<0.001$). Specifically, people who are unemployed/looking for work, disabled/not applicable/sheltered employment, and unknown had general higher scores than people who are workers, retired, students, homemakers. In addition, participants who are workers and retired had lower Neuroticism but higher Conscientiousness scores. Extraversion and Agreeableness did not show a clear pattern (Figure.14).

Figure.14. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in participants who were workers (W), retired (R), students (S), homemakers (H), unemployed/looking for work (U), disabled/not applicable/sheltered employment (D), and unknown (N/A) respectively. There were associations at various directions between occupation groups and all personality traits. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



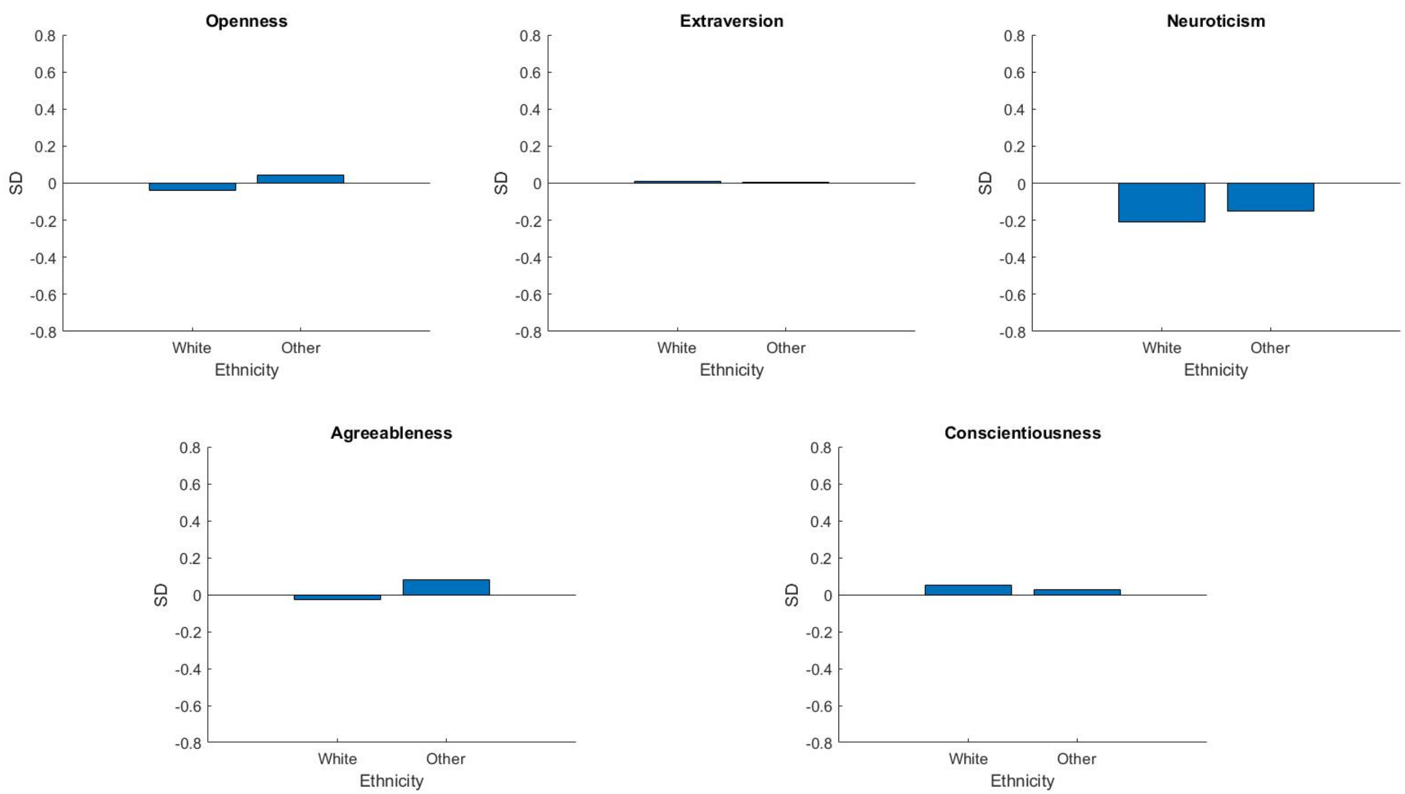
I found a significant effect of income on Openness ($F(11, 69{,}244)=2.44$, $p<0.01$), Extraversion ($F(11, 69{,}244)=21.01$, $p<0.001$), Neuroticism ($F(11, 69{,}244)=62.66$, $p<0.001$), Agreeableness ($F(11, 69{,}244)=24.26$, $p<0.001$), and Conscientiousness ($F(11, 69{,}244)=23.30$, $p<0.001$). Specifically, Openness, Extraversion, and Conscientiousness were positively related to income whereas Neuroticism and Agreeableness were negatively associated with income (Figure.15)

Figure.15. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in participants who had unknown income, £10-20K (1-2), £20-30K (2-3), £30-40K (3-4), £40-50K (4-5), £50-60K (5-6), £60-70K (6-7), £70-80K (7-8), £80-90K (8-9), £90-100K (9-10), >£100K (>10), and prefer not to say respectively. Income is associated with all personality traits with Openness, Extraversion, and Conscientiousness positively related to income and Neuroticism and Agreeableness negatively associated with income. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



Finally, there was a significant main effect of ethnicity on Extraversion ($F(1, 69{,}244)=1.81$, $p<0.05$), Neuroticism ($F(1, 69{,}244)=6.57$, $p=0.01$), and Agreeableness ($F(1, 69{,}244)=48.54$, $p<0.001$), but not on Openness nor Conscientiousness. However, the differences in personality traits between the two groups were quite small (Figure.16).

Figure.16. Personality traits including Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness in participants who were white European or North American and other race respectively. There was a significant effect of ethnicity on Extraversion, Neuroticism, and Agreeableness, but not on Openness nor Conscientiousness. Y axes = mean factor scores from the exploratory factor analysis (EFA) in SD units.



2.4.4. The effect of psychiatric and neurological conditions on personality

I found that there are increases in Openness ($t(4,853)=5.61$, $p<0.001$, Cohen's $d=0.11$, [95% CI: 0.06, 0.11]) and Neuroticism ($t(4,853)=50.46$, $p<0.001$, Cohen's $d=0.61$, [95% CI: 0.58, 0.63]) but decreases in Extraversion ($t(4,853)=-2.74$, $p<0.01$, Cohen's $d=-0.04$, [95% CI: -0.07, -0.01]), Agreeableness ($t(4,853)=-1.98$, $p<0.05$, Cohen's $d=-0.03$, [95% CI: -0.06, 0.00]), and Conscientiousness($t(4,853)=-14.79$, $p<0.001$, Cohen's $d=-0.21$, [95% CI: -0.24, -0.18]) actual scores in patients with depression comparing to what the model would predict by their demographics.

In patients with anxiety only, Openness ($t(4,681)=8.45$, $p<0.001$, Cohen's $d=0.13$, [95% CI: 0.10, 0.16]) and Neuroticism ($t(4,681)=73.46$, $p<0.001$, Cohen's $d=0.84$, [95% CI: 0.82, 0.86]) scores were larger whereas Agreeableness ($t(4,681)=-5.41$, $p<0.001$, Cohen's $d=0.08$, [95% CI: 0.05, 0.11]) and Conscientiousness($t(4,681)=-5.81$, $p<0.001$, Cohen's $d=-0.08$, [95% CI: -0.11, -0.06]) scores were smaller than what the model would predict by their demographics.

However, in people with both depression and anxiety, the differences of component scores were positive in Openness ($t(6,046)=10.97$, $p<0.001$, Cohen's $d=0.15$, [95% CI: 0.12, 0.18]), Neuroticism ($t(6,046)=102.35$, $p<0.001$, Cohen's $d=1.05$, [95% CI: 1.03, 1.07]), Agreeableness ($t(6,046)=4.26$, $p<0.001$, Cohen's $d=0.06$, [95% CI: 0.03, 0.08]) but negative in Extraversion ($t(6,046)=-10.31$, $p<0.001$, Cohen's $d=-0.13$, [95% CI: -0.16, -0.11]) and Conscientiousness ($t(6,046)=-15.31$, $p<0.001$, Cohen's $d=-0.20$, [95% CI: -0.23, -0.17]). In patients with ADHD, Openness ($t(367)=7.49$, $p<0.001$, Cohen's $d=0.50$, [95% CI: 0.37, 0.63]), Extraversion($t(367)=7.09$, $p<0.001$, Cohen's $d=0.37$, [95% CI: 0.27, 0.47]), and Neuroticism ($t(367)=11.92$, $p<0.001$, Cohen's $d=0.65$, [95% CI: 0.54, 0.76]) were significantly larger from what the model would predict by their demographics. The effect on Conscientiousness scores

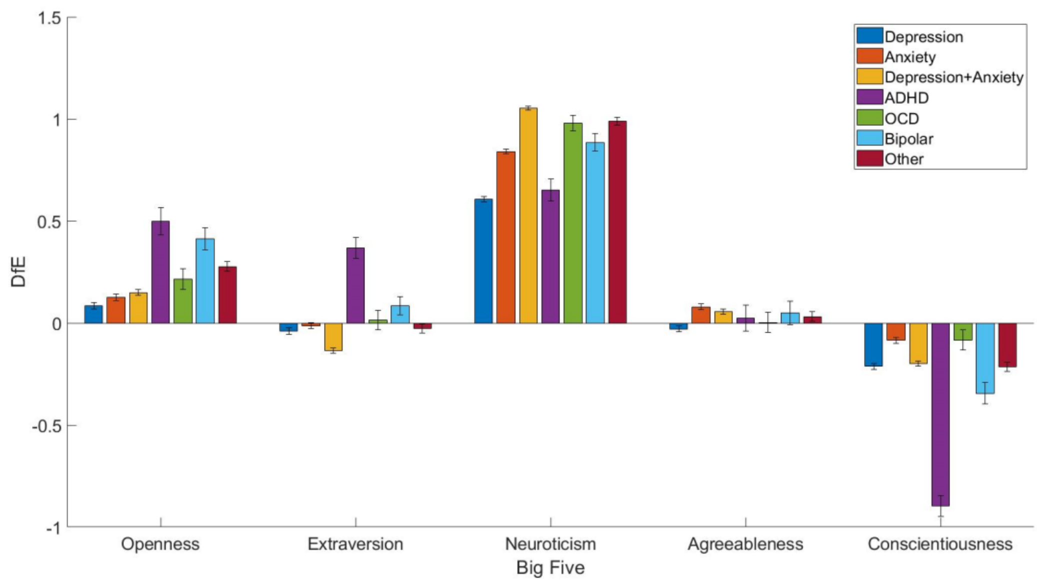
($t(367)=-17.64$, $p<0.001$, Cohen's $d=-0.09$, [95% CI: -1.00, -0.80]) was in the opposite direction.

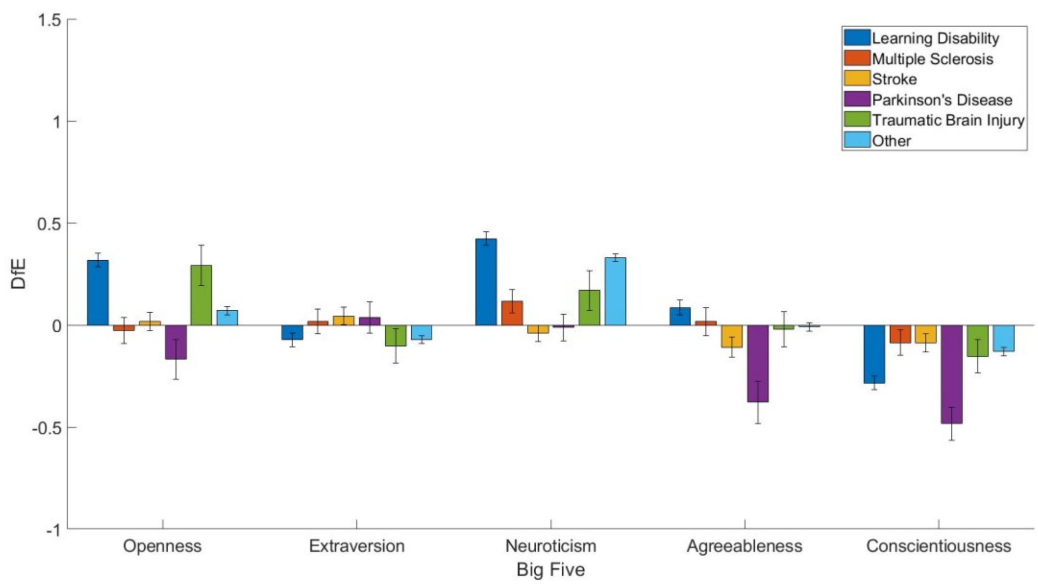
In patients with OCD, I found that only Openness ($t(798)=5.50$, $p<0.001$, Cohen's $d=0.22$, [95% CI: 0.14, 0.29]) and Neuroticism ($t(798)=32.97$, $p<0.001$, Cohen's $d=0.98$, [95% CI: 0.92, 1.04]) actual scores were significantly larger but Conscientiousness ($t(798)=-2.19$, $p<0.05$, Cohen's $d=-0.08$, [95% CI: -0.16, -0.01]) score was significantly smaller from what the model would predict by their demographics. However, we did not find a significant difference between observed and predicted in Extraversion and Agreeableness. For bipolar patients, Openness ($t(452)=7.56$, $p<0.001$, Cohen's $d=0.41$, [95% CI: 0.30, 0.52]) and Neuroticism ($t(452)=20.97$, $p<0.001$, Cohen's $d=0.89$, [95% CI: 0.80, 0.97]) actual scores were larger than what the model would predict by their demographics but the direction of this effect was negative in Conscientiousness score ($t(367)=-6.58$, $p<0.001$, Cohen's $d=-0.34$, [95% CI: -0.45, -0.24]).

Finally, there were significant positive differences between the actual component scores and what would be predicted by their demographics in Openness ($t(2{,}304)=11.82$, $p<0.001$, Cohen's $d=0.28$, [95% CI: 0.23, 0.32]) and Neuroticism ($t(2{,}304)=53.12$, $p<0.001$, Cohen's $d=0.99$, [95% CI: 0.95, 1.02]), but negative difference in Conscientiousness ($t(2{,}304)=-9.68$, $p<0.001$, Cohen's $d=-0.22$, [95% CI: -0.26, -0.17]) score in patients with other psychiatric conditions expect for Extraversion and Agreeableness. Effect size in standard deviation from expected (DfE) units is visualized in Figure.17.

As for the neurological condition group, we found that Openness ($t(977)=9.42$, $p<0.001$, Cohen's $d=0.32$, [95% CI: 0.25, 0.38]), Neuroticism ($t(977)=12.68$, $p<0.001$, Cohen's $d=0.42$, [95% CI: 0.36, 0.49]), and Agreeableness ($t(977)=2.37$, $p<0.05$, Cohen's $d=0.09$, [95% CI: 0.01, 0.16]) actual scores were significantly more, but Extraversion ($t(4{,}853)=-2.17$, $p<0.05$, Cohen's $d=-0.07$, [95% CI: -0.14, -0.01]) and Conscientiousness ($t(977)=-8.46$, $p<0.001$, Cohen's $d=-0.28$, [95% CI: -0.35, -0.22]) scores were significantly less in patients with learning disability than what the model would predict by their demographics except for Extraversion. However, in patients with multiple sclerosis, only Neuroticism ($t(297)=2.08$, $p<0.05$, Cohen's $d=0.12$, [95% CI: 0.01, 0.23]) score was bigger than what would be predicted by their demographics according to the model. In patients with stroke, only Agreeableness ($t(494)=-2.22$, $p<0.05$, Cohen's $d=-0.11$, [95% CI: -0.21, -0.01]) and Conscientiousness ($t(494)=-1.98$, $p<0.05$, Cohen's $d=-0.09$, [95% CI: -0.17, -0.00]) were significantly less than what would be predicted. Similarly, in patients with Parkinson's disease, only Agreeableness ($t(158)=-3.71$, $p<0.001$, Cohen's $d=-0.38$, [95% CI: -0.58, -0.18]) and Conscientiousness ($t(158)=-6.01$, $p<0.001$, Cohen's $d=-0.48$, [95% CI: -0.64, -0.32]) actual scores were smaller from what the model would predict by their demographics. In patients with traumatic brain injury, only Openness ($t(123)=2.96$, $p<0.01$, Cohen's $d=0.29$, [95% CI: 0.10, 0.49]) score was more than expected. Finally, in patients with other neurological conditions, personality traits including Openness ($t(2,603)=3.32$, $p<0.001$, Cohen's $d=0.07$, [95% CI: 0.03, 0.11]) and Neuroticism ($t(2,603)=16.82$, $p<0.001$, Cohen's $d=0.33$, [95% CI: 0.29, 0.37]) scores were larger, whereas Extraversion ($t(2,603)=-3.69$, $p<0.001$, Cohen's $d=-0.07$, [95% CI: -0.11, -0.03]) and Conscientiousness ($t(2,603)=-6.27$, $p<0.001$, Cohen's $d=-0.13$, [95% CI: -0.17, -0.09]) scores were smaller than predicted scores in patients with learning disability. Effect size in standard deviation from expected (DfE) units is visualized in Figure.17.

Figure.17. The effect size of psychiatric and neurological conditions on personality. There are increases in Openness and Neuroticism scores across all psychiatric and neurological groups with consistent decreases in Conscientiousness scores. However, the relationships between neurological conditions and personality traits are generally weaker than the relationships between psychiatric conditions and personality. Y axes= Effect size in standard deviation from expected (DfE) units.





2.5. Discussion

My study validated the 18-item Big Five I developed based on data at large scale. Moreover, my study is the first study that applied such a shortened and validated scale to assess the differential sensitivity of personality traits to clinical groups with psychiatric conditions. My results showed that the 18-item Big Five has higher validity coefficients and test-retest reliability than any other shortened Big Five available. In addition, different personality traits may be affected differently by various psychiatric and neurological conditions, but the main trends are that Openness, Extraversion, and Neuroticism are positively affected whereas Agreeableness and Conscientiousness are negatively affected.

My shortened version of the Big Five personality inventory only consists of 18 items. Moreover, the validity of such a short inventory was confirmed through the correlation between component scores calculated based on full-scale Big Five and the little Big Five. The part-whole correlations of Openness, Extraversion, Neuroticism, Agreeableness, and Conscientiousness were all quite strong, which are higher than a 10-item scale (Rammstedt et al., 2007), a 15-item scale (Hahn et al., 2012), a 20-item scale and a 32-item scale. In addition, I also observed higher test-rest reliability across two time points than a 10-item scale (Rammstedt et al., 2007) and a 15-item scale (Hahn et al., 2012). Thus, to my best knowledge, my shortened scale of the Big Five is by far the psychometrically strongest shortened version of the Big Five. Using a smaller number of items could avoid measurement error (Laros et al., 2018), and can reduce discouragement, fatigue, and inattention in participants, especially in clinical groups.

Indeed, I applied my Big Five to clinical groups with psychiatric and neurological conditions using a predictive normative modelling approach by taking the effects of demographics into account. Consistent with many other studies (e.g., Dahmann & Anger, 2014; Denissen et al., 2018; Mann et al., 2021; Stake & Eisele, 2010), demographics including age, gender, education, occupation, and income were significant predictors of dimensions of personality. However, there seemed to be inconsistent results of the effect of language, country of residence, and ethnicity across domains of personality. Specifically, language was a significant predictor for Openness, Neuroticism, and Conscientiousness but not for Extraversion and Agreeableness. Country of residence could predict Openness and Conscientiousness but not Extraversion, Neuroticism, or Agreeableness. Finally, ethnicity was a significant predictor for Extraversion, Neuroticism, and Conscientiousness but not for Openness and Agreeableness.

Regarding the relationships between the Big Five and psychiatric conditions, I found that Openness and Neuroticism are positively related to depression whereas Extraversion, Agreeableness, and Conscientiousness were negatively related to depression. However, Extraversion did not associate with depression. The findings that Openness is positively associated with depression and Agreeableness was negatively associated with depression seem to be inconsistent with Hakulinen et al. (2015), which found that low Extraversion, high Neuroticism, and low Conscientiousness are associated with depressive symptoms. This could be explained by the fact that previous studies assessed their depressive symptoms. However, in the current study, I asked participants to indicate what psychiatric conditions they have. I also had very big data and are able to take lots of potential demographic confounds into account. As for patients with anxiety only, both Openness and Neuroticism scores are significantly higher than their predicted scores. The finding of increased Openness, intact Extraversion, and decreased Agreeableness seems to be contradictory to a previous study (Karsten et al., 2012), which found that only Neuroticism increases during an anxiety episode but not other personality traits. Discrepancies could be explained by the fact that Karsten et al. (2012) assessed anxiety symptoms rather than simply asking if they have any psychiatric disorders. Moreover, Karsten et al. (2012) is a longitudinal study.

Four dimensions of personality were significantly different from what they were and what would be predicted by demographics in patients reported with both depression and anxiety. There were increases in Openness, Extraversion, and Neuroticism but decreases in Conscientiousness in ADHD patients, which seemed to be consistent and inconsistent with previous studies (e.g., Perroud et al., 2016) that found that Novelty Seeking, Harm Avoidance, and Self-Tendency scores are positive whereas low Self-Directedness and Cooperativeness (a facet of Agreeableness; De Fruyt et al., 2000) scores are negatively associated with ADHD diagnosis. In patients with OCD, I found positive associations between Openness and Neuroticism and OCD and a negative relationship between Conscientiousness and OCD, which seems to be consistent and inconsistent with Fardin et al. (2017), which found a positive relationship between Neuroticism and the Maudsley Obsessive-Compulsive Inventory (MOCI) and negative associations between Openness, Agreeableness, and Conscientiousness and the MOCI. Again, this difference may be explained by the small sample size and the fact that Fardin et al. (2017) used MOCI to measure the degree of OCD. Regarding patients with bipolar disorder, Openness and Neuroticism were positively affected whereas Conscientiousness was negatively affected. Similarly, in patients with other neurological conditions, there were increased Openness and Neuroticism but decreased Conscientiousness scores. However, other traits including Extraversion and Agreeableness remained intact.

As for the neurological condition group, Openness, Neuroticism, and Agreeableness in patients with learning disability were significantly more than the scores that would be predicted by their demographics whereas actual Extraversion and Conscientiousness scores were less than the predicted scores. However, in patients with multiple sclerosis, only the actual Neuroticism score was more than the score that would be predicted by their demographics according to the model, which seems to be consistent with Abedini et al. (2012). In patients with stroke, there were decreased Agreeableness and Conscientiousness actual scores (Dwan & Ownsworth, 2019). I also find that in patients with Parkinson's disease, Agreeableness and Conscientiousness were decreased but did not find lower levels of Openness and Extraversion (Santangelo et al., 2018). In patients with traumatic brain injury (TBI), only Openness scores were significantly higher than what would be expected. Finally, in patients with other neurological conditions, there were increases in Openness and Neuroticism, but decreases in Extraversion and Conscientiousness. In sum, there were discrepancies in the results between the current study and previous studies, which could be explained mainly by four reasons: (1) I had a very large sample size compared to the small sample sizes in previous studies (N=87,983). For instance, Fardin et al. (2017) had only 227 university students from Iron, Karsten et al. (2012) had 2596 participants from the Netherland, and Perround et al. (2019) had only 89 participants with ADHD patients and 403 individuals in the comparison group. (2) I adopted a predictive normative modeling approach, which could take demographics into account while investigating how the Big Five in patients were affected. (3) Some of the previous studies assessed symptoms and severity (e.g., Fardin et al., 2017; Karsten et al., 2012; Preround et al., 2019) rather than simply asking participants to indicate if they have one or more of the following psychiatric and neurological conditions. (4) Some of the previous studies adopted a longitudinal approach (i.e., Hakulinen et al., 2015; Karsten et al., 2012) whereas my study is cross-sectional.

Looking at these relationships profilewise, I found that there were increases in Openness and Neuroticism scores across all psychiatric groups with consistent decreases in Conscientiousness scores. Extraversion and Agreeableness scores were sometimes larger and sometimes smaller than predicted scores. There are several ways that may explain the associations between personality traits and psychiatric conditions. For instance, people who are high in Openness and Neuroticism but low in Conscientiousness are at a higher risk of substance abuse (e.g., Kang, 2022b), which posits them under an increased risk of developing psychiatric conditions. In addition, there are shared genetic factors between personality traits and psychopathology (Carey & DiLalla, 1994). Specifically, genes accounted for more than 50% of the observed relationship between Neuroticism and symptoms of depression and anxiety (Carey & DiLalla, 1994). Finally, underlying neural basis of personality traits can explain this link. For instance, Neuroticism and Conscientiousness are closely related to the prefrontal cortex, whereas the prefrontal cortex is closely connected with psychiatric conditions. Personality traits in neurological groups roughly followed the same pattern but were less likely to differ from expected scores depending on the types of neurological conditions. However, the relationships between neurological conditions and personality traits were generally weaker than the relationships between psychiatric conditions and personality.

To conclude, my study provided a well-validated but short scale of the Big Five with high validity and test-retest reliability and showed its application in clinical populations. Given its strength, limitations include (1) participants self-reported their psychiatric and neurological conditions, which can be subject to bias. Specifically, there might be instances where participants who had these conditions reported that they had not as they had not had a chance to see a doctor. Thus, it is possible that I missed participants who actually had psychiatric/neurological condition, which may weaken the associations I found in this study. (2) This is a cross-sectional study that prevents us from finding the causal relationship between psychological and neurological disorders and personality change. Thus, it is sensible for future studies to assess personality traits before and after these disorders to establish causality. (3) This study focused on a sample from the United Kingdom and focused on the psychiatric and neurological population, which may make it hard to generalize to the broader population, including other countries, cultures, and clinical populations. Future studies should validate this short Big Five in other cultures and other clinical populations to ensure its generalisability.

2.6. Supplementary material

Table.1. Demographic information of the participants of Dataset 3.

Variables	Mean	S.D.
Age	46.58	15.84
	Count	%
Handedness		
Right-handed	76226	86.64
Left-handed	9480	10.77
Ambidextrous	2277	2.59
Gender		
Male	48717	55.37
Female	38876	44.19
Other	390	0.44
Language		
English	82371	93.62
Other	5612	6.38
Ethnicity		
White European or North American	80456	91.44
Other	7527	8.56
Country		
United Kingdom	80539	91.54
Other	7444	8.46
Education		
University degree	51088	58.07
Secondary school/High school diploma	31406	35.70
PhD	3595	4.09
Primary/Elementary school	1772	2.01
No schooling	122	0.14
Income		
£10-20K	9175	10.43
£20-30K	11806	13.42
£30-40K	10513	11.95
£40-50K	7413	8.43
£50-60K	4399	5.00
£60-70K	2598	2.95
£70-80K	1877	2.13
£80-90K	1192	1.35
£90-100K	1143	1.30
>100K	3395	3.86
Unknown	31358	35.64
Prefer not to say	2107	2.39

Table.1. Selected personality items based on the heaviest loadings.

I see myself as someone who is talkative.
I see myself as someone who does a thorough job.
I see myself as someone who is original, comes up with new ideas.
I see myself as someone who is reserved.
I see myself as someone who is relaxed, handles stress well.
I see myself as someone who has a forgiving nature.
I see myself as someone who tends to be disorganized.
I see myself as someone who worries a lot.
I see myself as someone who tends to be quiet.
I see myself as someone who is emotionally stable, not easily upset.
I see myself as someone who is inventive.
I see myself as someone who perseveres until the task is finished.
I see myself as someone who values artistic, aesthetic experiences.
I see myself as someone who is considerate and kind to almost everyone.
I see myself as someone who likes to reflect, play with ideas.
I see myself as someone who has few artistic interests.
I see myself as someone who likes to cooperate with others.
I see myself as someone who is sophisticated in art, music, or literature.

Table.2. The 5-item version of the Big Five selected based on the heaviest loading question for each factor.

I see myself as someone who tends to be quiet.
I see myself as someone who worries a lot.
I see myself as someone who does a thorough job.
I see myself as someone who is inventive.
I see myself as someone who is considerate and kind to almost everyone.

Table.3. The 10-item version of the Big Five proposed by Rammstedt et al. (2007).

I see myself as someone who tends to find fault with others.
I see myself as someone who does a thorough job.
I see myself as someone who is reserved.
I see myself as someone who is relaxed, handles stress well.
I see myself as someone who has an active imagination.
I see myself as someone who is generally trusting.

I see myself as someone who tends to be lazy.

I see myself as someone who values artistic, aesthetic experiences.

I see myself as someone who is outgoing, sociable.

I see myself as someone who gets nervous easily.

Table.4. Items in the full-scale Big Five Inventory and their corresponding loadings in the factor analysis for training set.

1	I see myself as someone who is talkative
2	I see myself as someone who tends to find fault with others
3	I see myself as someone who does a thorough job
4	I see myself as someone who is depressed, blue
5	I see myself as someone who is original, comes up with new ideas
6	I see myself as someone who is reserved
7	I see myself as someone who is helpful and unselfish with others
8	I see myself as someone who can be somewhat careless
9	I see myself as someone who is relaxed, handles stress well
10	I see myself as someone who is curious about many different things
11	I see myself as someone who is full of energy
12	I see myself as someone who starts quarrels with others
13	I see myself as someone who is a reliable worker
14	I see myself as someone who can be tense
15	I see myself as someone who is ingenious, a deep thinker
16	I see myself as someone who generates a lot of enthusiasm
17	I see myself as someone who has a forgiving nature
18	I see myself as someone who tends to be disorganized
19	I see myself as someone who worries a lot
20	I see myself as someone who has an active imagination
21	I see myself as someone who tends to be quiet
22	I see myself as someone who is generally trusting
23	I see myself as someone who tends to be lazy
24	I see myself as someone who is emotionally stable, not easily upset
25	I see myself as someone who is inventive
26	I see myself as someone who has an assertive personality
27	I see myself as someone who can be cold and aloof
28	I see myself as someone who perseveres until the task is finished
29	I see myself as someone who can be moody
30	I see myself as someone who values artistic, aesthetic experiences
31	I see myself as someone who is sometimes shy, inhibited
32	I see myself as someone who is considerate and kind to almost everyone
33	I see myself as someone who does things efficiently
34	I see myself as someone who remains calm in tense situations
35	I see myself as someone who prefers work that is routine
36	I see myself as someone who is outgoing, sociable
37	I see myself as someone who is sometimes rude to others
38	I see myself as someone who makes plans and follows through with them

39	I see myself as someone who gets nervous easily
40	I see myself as someone who likes to reflect, play with ideas
41	I see myself as someone who has few artistic interests
42	I see myself as someone who likes to cooperate with others
43	I see myself as someone who is easily distracted
44	I see myself as someone who is sophisticated in art, music, or literature

	Extraversion	Neuroticism	Conscientiousness	Openness	Agreeableness
1	-0.7743	0.1834	-0.0583	-0.0007	0.0792
2	-0.0977	0.2146	0.1412	0.0428	-0.4872
3	0.0587	0.1516	0.6922	0.0562	0.0103
4	0.0973	0.5781	-0.0937	0.0674	-0.0582
5	-0.0252	-0.1178	0.0140	0.7314	-0.0961
6	0.8436	-0.0001	0.0728	0.0793	0.0043
7	-0.0194	0.0914	0.1303	0.0815	0.5184
8	-0.0935	-0.0070	-0.5349	0.1072	-0.1084
9	0.0926	-0.7849	-0.0443	0.1126	0.0070
10	0.0184	-0.0435	-0.0170	0.4936	0.0070
11	-0.2479	-0.2118	0.1875	0.1857	0.0243
12	-0.2125	0.1449	-0.0252	0.0776	-0.5031
13	0.0419	0.0670	0.5589	-0.0321	0.1448
14	0.0010	0.7137	0.1398	0.0687	-0.1318
15	0.1726	0.0189	0.0798	0.6347	-0.0827
16	-0.4347	-0.0120	0.1012	0.3016	0.1528
17	0.0303	-0.0686	-0.1416	0.0551	0.5766
18	-0.0075	-0.0104	-0.6883	0.1478	0.0707
19	-0.0003	0.8324	0.0768	-0.0050	0.1114
20	-0.0231	0.1552	-0.0857	0.6027	0.0539
21	0.9175	-0.0586	0.0567	0.0905	0.0494
22	-0.0422	-0.0002	-0.0118	-0.0240	0.4276
23	0.0955	-0.0036	-0.5726	0.0387	-0.0833
24	0.1211	-0.7208	0.0179	0.0636	0.0355
25	0.0689	-0.1484	0.0107	0.7686	-0.0929
26	-0.4550	-0.1219	0.1904	0.2175	-0.2974
27	0.3400	-0.0672	0.0206	0.1532	-0.5447
28	0.0690	0.0667	0.6497	0.1127	0.0239
29	0.0204	0.4268	-0.0170	0.0716	-0.3164
30	0.0037	0.1686	-0.0490	0.4235	0.2045
31	0.7341	0.1567	-0.0198	0.0770	0.0737
32	-0.0034	0.1475	0.0637	0.0347	0.6975
33	0.0555	-0.0163	0.6448	0.0909	-0.0269
34	0.1092	-0.5393	0.1086	0.1841	0.0432
35	0.0875	0.2107	0.1255	-0.2713	0.0622
36	-0.7132	-0.0334	-0.0284	0.0070	0.1552
37	-0.1045	0.0344	-0.0586	0.1159	-0.6186
38	-0.0398	0.0011	0.5979	0.0539	-0.0298

39	0.1854	0.6612	-0.0169	-0.0597	0.1369
40	0.1583	0.0228	-0.0267	0.5887	0.0677
41	0.0062	-0.0772	0.0391	-0.3299	-0.1383
42	-0.1333	0.0635	0.0737	-0.0391	0.4896
43	-0.0809	0.1479	-0.5319	0.0944	0.0138
44	-0.0080	0.0908	-0.0416	0.4125	0.0955

Chapter 3

Understanding the Mechanisms of Intentional Learning: “What” and “How”?

3.1. Abstract

Intentional learning refers to goal-directed or motivated acquisition of knowledge, skills, or understanding. There are several types of intentional learning in literature including instruction-based learning (IBL), observational learning (OL), and reinforcement learning (RL). Task complexity is one of the important factors that influence intentional learning. Yet, there are mainly three types of task complexity in the intentional learning literature including simple, complex, and model-based. The aim of the current study is to investigate if individual differences in intentional learning can be captured by the type of intentional learning and the complexity of intentional learning. I developed 9 intentional learning tasks across different types and complexity levels. I then collected data of these tasks by emailing people who have participated The Great British Intelligence Test. Among people who have participated in my study, there were 113 participants who completed all the intentional learning tasks. Repeated-measure analysis of variances (RANOVAs) and a permutation test was used to analyze the data. The RANOVA revealed that there is a significant stage*task*complexity interaction on accuracy and reaction time (RT). Similarly, there was a significant block*task*complexity interaction on accuracy and RT. RANOVAs on accuracy and RT of individual tasks revealed a general learning trend as indicated by decreased RT but few learning trends in increased accuracy. The permutation test showed the probability that the model of interrelationships between the tasks provides a better explanation of the data than other possible models of the same structural properties for accuracy, RT, and learning rate of RT across stages and blocks but not for learning rate of accuracy across stages and blocks. This study provided compelling evidence regarding the construct validity of these tasks to capture "what" and "how" in intentional learning.

3.2. Introduction

Intentional learning is goal-directed or motivated acquisition of knowledge, skills, or understanding whereas incidental learning refers to the acquisition of knowledge, skills, or understanding without goals or intention (Scardamalia & Marlene, 1989). There are several well-documented forms of intentional learning including but not limit to instruction-based learning (IBL; e.g., Cole et al., 2016; Hampshire et al., 2016, 2019; Ruge et al., 2019), reinforcement learning (RL; e.g., Daw et al., 2011; Gläscher et al., 2010), and observational learning (OL; Burke et al., 2010; Monfardini et al., 2008, 2013). The commonality across different types of intentional learning is the fact that they all require the learner to acquire the stimulus-response (S-R) association, but the way the S-R associations differ in different types of intentional learning. Specifically, instruction-based learning (IBL, sometimes also termed rapid instruction-based task learning, "RITL") is the ability to learn to perform tasks based on explicit instructions rapidly. Tasks also can be learned from reinforcement learning (RL), where participants learn from receiving feedback (Cole et al., 2013). Observational learning refers to learning by watching others' actions and outcomes in certain circumstances. Unlike imitation, observational learning does not just require the learning to replicate an action. Rather, one has to understand the intentions and associations, and from there have a model for performing the task (Kang et al., 2021).

Task complexity is one of the important factors that influence human behaviour and performance both in real-life scenarios and in the laboratory. For instance, in decision-making research, even if people pretended to integrate possibilities, Tversky and Kahneman (1981) found that the maintained intricacy of practical problems in decision tasks would prohibit them from doing so. Payne (1976) discovered that task complexity was a key determinant of decision process and strategy: decision-makers used a compensatory decision process (a method that involves identifying a set of attributes applicable to the decision, assigning relative importance or weight to each attribute, computing an overall score for each option based on the attribute weight, and selecting the option with the best score) when faced with a low-complexity task, whereas they used a non-compensatory process and focused on selective information when faced with a high-complexity task. Lussier and Olshavsky (1979) and Kim and Khoury (1987) found similar results. In the goal-setting area, involving the development of an action plan designed in order to motivate and guide a person or group toward a goal, Wood et al. (1987) and Campbell (1991) identified task difficulty as a consistent moderator of the goal-setting effect. In this case, the goal-setting system represents a decision-making process designed to effectively achieve self-determined objectives through a series of action and behaviour strategies to be performed. They concluded that goal setting improves task performance the most for low-complexity tasks and the least for high-complexity tasks (Campbell, 1991; Wood et al., 1987).

There are several forms of task complexity in the intentional learning literature. One type of task complexity is the number of S-R associations to be remembered (e.g., Parkin et al., 2021; Ruge & Wolfensteller, 2019). Specifically, in this sense, a more complex task would require a greater number of S-R associations to be remembered and conjointly applied in a task whereas a less complex task would require a smaller number of S-R associations to be remembered. Participants tend to make more mistakes in more complex tasks compared to less complex tasks (Ruge & Wolfensteller, 2019). On the other hand, the theoretical framework has also considered two types of learning as model-free and model-based (Daw et al., 2005; Doya et al., 2002). Specifically, in model-based learning, a cognitive model describes how different “states” or situations of the world relate to each other. By contrast, model-free learning learns the stimulus-response (S-R) directly without building such a model. One well-established example is model-based and model-free RL (e.g., Daw et al., 2005; Doya et al., 2002).

Taken together, previous studies have investigated the neural basis of different forms of intentional learning, and how task complexity might play a role in brain-behaviour associations. However, from a behavioural level, few studies have compared the performance as indicated by the accuracy, reaction time (RT), and learning rate across these different types of intentional learning. Moreover, another question is whether different types of intentional require the same or distinct ability across different levels of task complexity. Thus, the aim of the current study is to investigate if individual differences in intentional learning can be captured by the type of intentional learning and the complexity of intentional learning. I hypothesise that (1) there is a within-subject effect of intentional learning as indicated by increased accuracy with time accompanied by decreased RT, (2) there is a between-subject effect of intentional learning that can be explained by the type of intentional learning and the complexity of intentional learning, which could reflect differences in the types of learning that or other people are more able to cope with.

3.3. Methods

3.3.1. Data collection

I collected the data from members of the general public, predominantly from the UK, who have participated in previous studies but opted into the current study via The Great British Intelligence Test, a collaborative citizen science project with BBC2 Horizon that launched in late December 2019. I recontacted them via email and asked them if they would like to participate in my intentional learning studies. The data analyzed here include responses from June through

August 2022, which included 113 participants who completed all the intentional learning tasks (i.e., participants with any missing values were removed). This study was approved by the Imperial College Research Ethics Committee (17IC4009). Participants provided informed consent via the study website prior to starting the assessment.

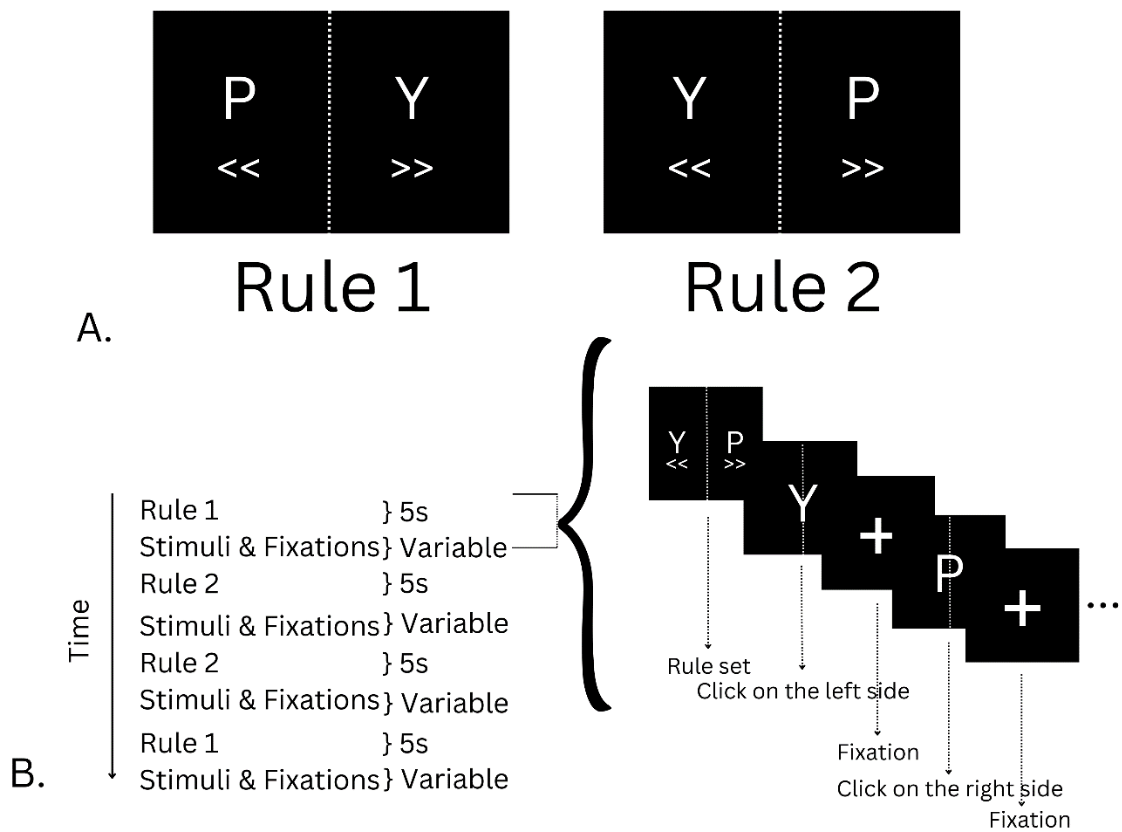
3.3.2. Task design

All Cognitron learning tasks were coded in HTML5 with JavaScript by WK and WT. They were hosted on a custom server system (Cognitron) on the Amazon EC2 that can support diverse studies via custom websites. The server system was specifically developed to handle spikey acquisition profiles that are characteristic of main-stream media collaborative studies, fitting the number of server instances in an automated manner to rapid changes in demand. Tasks were presented in random order.

3.3.2.1. Instruction-based learning (IBL)

The IBL task was developed based on paradigms used in previous neuroimaging research of IBL (e.g., Hampshire et al., 2016, 2019; Parkin et al., 2021). Specifically, participants were required to learn two binary S-R rules over 4 continuous learning blocks (i.e.,“Y” =click on the left side and “P” = click on the right side and “P” =click on the left side and “Y” = click on the right side). Each block started with a slide that shows one of the S-R rules, which lasted 5s. The subsequent practice stage began after the rule disappeared. During the practice stage, participants were required to make a response by clicking on the left or the right side of the box separated by the midline. There were 2 stimuli per rule repeating 6 times in each block with no feedback given after a response was made. Stimuli were presented in pseudo-randomized order. The fixation followed by the next stimulus displayed on the screen once participants made a response (Figure.18).

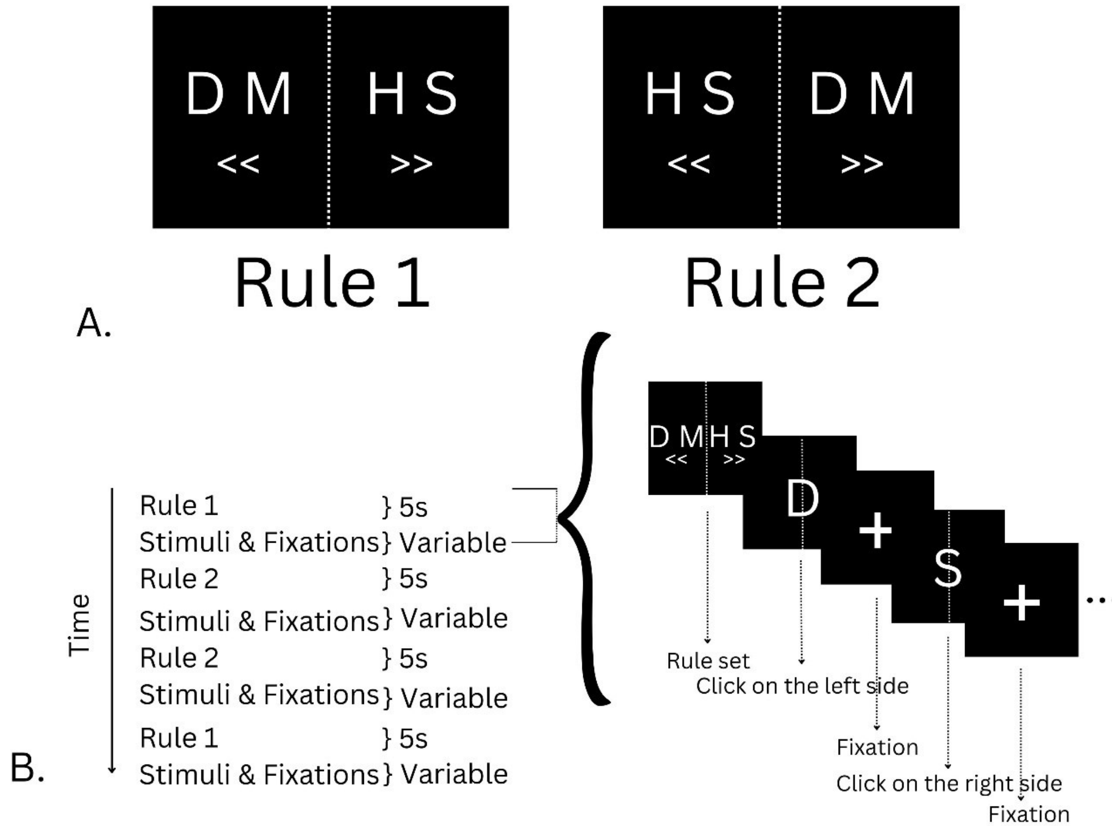
Figure.18. The outline of the instruction-based learning (IBL) task. A. The two binary discrimination rule slides. B. Task structure, including 2 discrimination rules over 4 blocks with two stimuli per rule repeating 6 times.



3.3.2.2. Complex instruction-based learning (CIBL)

Similarly, the CIBL task was based on several paradigms used in previous neuroimaging research of IBL (e.g., Hampshire et al., 2016, 2019; Parkin et al., 2021; Walfensteller & Ruge, 2019). Specifically, participants were required to learn 2 quaternary S-R rules but with 4 possible combinations per rule over 4 continuous learning blocks (i.e., “D” or “M” =click on the left side and “H” or “S” = click on the right side and “H” or “S” =click on the left side and “D” or “M” = click on the right side). Each block started with a slide that shows one of the S-R rules, which lasted 5s. The subsequent practice stage began after the rule disappeared. During the implementation stage, participants were required to make a response by clicking on the left or the right side of the box separated by the midline. There were 4 stimuli per rule repeating 3 times in each block with no feedback given after a response was made. Stimuli were presented in pseudo-randomized order. The next stimulus was displayed on the screen once participants made a response (Figure.19).

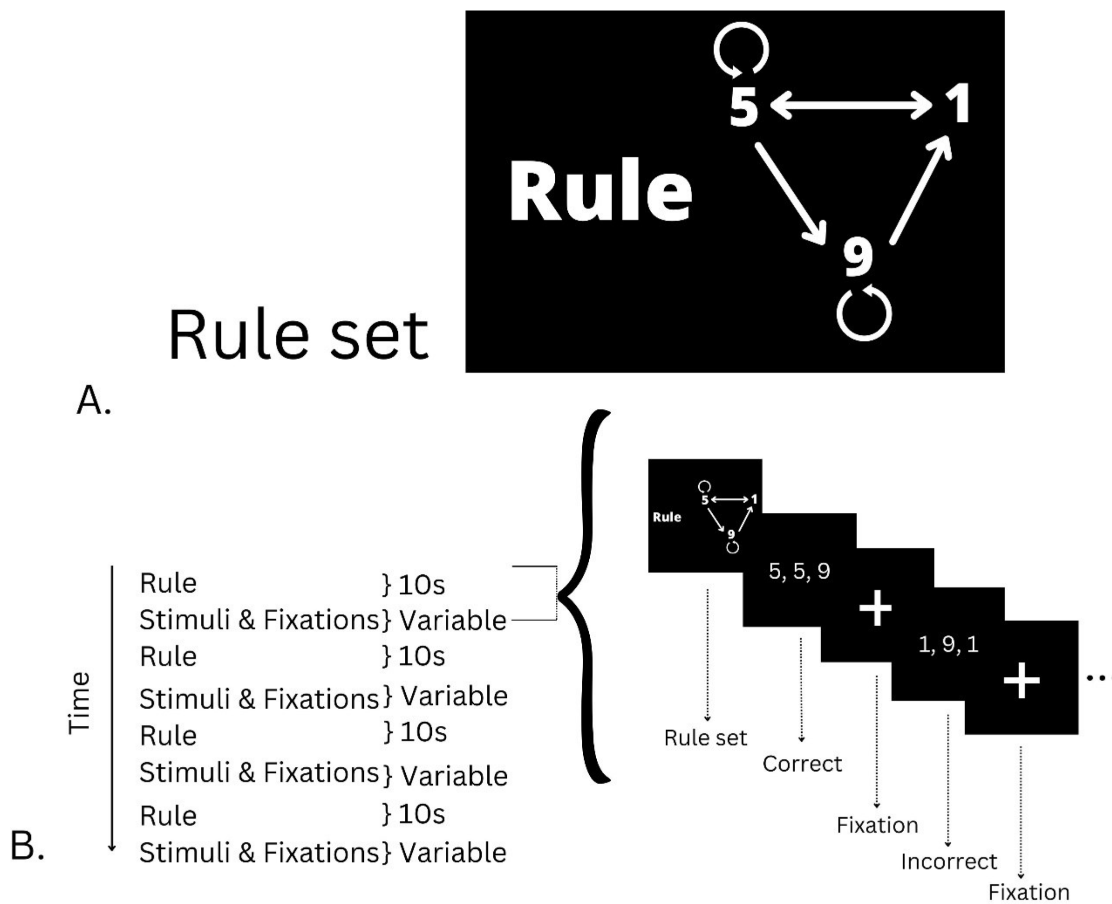
Figure.19. The outline of the complex instruction-based learning (CIBL) task. A. The 2 quaternary discrimination rule slides. B. Task structure, including 2 discrimination rules over 4 blocks with 4 stimuli per rule repeating 3 times.



3.3.2.3. Model-based instruction-based learning (MBIBL)

The MBIBL task was developed based on the artificial grammar task learning paradigm (Miller, 1958). Specifically, in the instruction phase that lasts for 10s, participants were asked to follow the rules for the pairing of numbers presented in the model. During the implementation stage, participants were asked to determine if the pseudo-randomly combined digits ranging from 2 to 4 digits as "ruleful" (i.e., correct) or "unruleful" (i.e., incorrect) by clicking on the corresponding button. There were 4 blocks in total with 12 trails in each block. Stimuli were presented in pseudo-randomized order and each stimulus only appeared once. The next stimulus was displayed on the screen once participants made a response, and there was no feedback after a response was made (Figure.20).

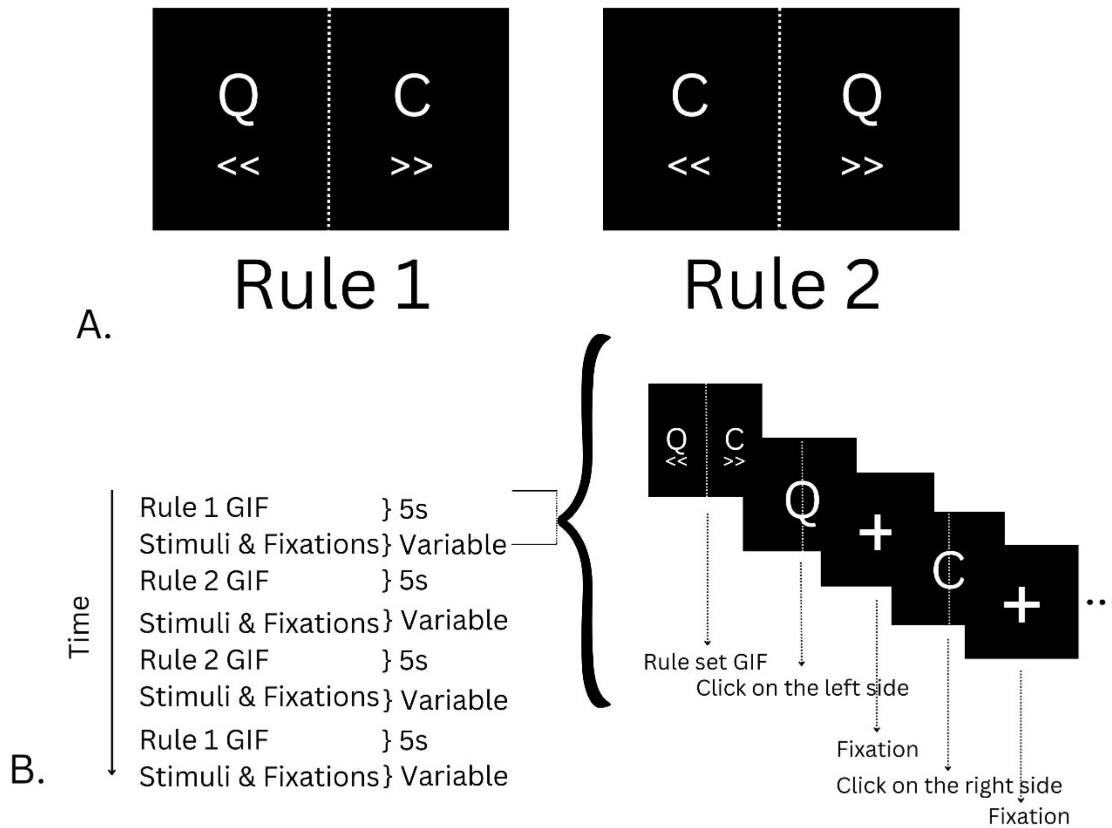
Figure.20. The outline of the model-based instruction-based learning (MBIBL) task. A. The model-based rule slide. B. Task structure, including one model-based rule over 4 blocks with 48 stimuli per rule with no repeating.



3.3.2.4. Observational learning (OL)

The main difference that exists between OL and IBL was the way rules are learned in the instruction phase. Unlike IBL, in the instruction phase of the OL, participants viewed a premade video clip in GIF format regarding how another person is performing the task. This task was inspired by several tasks used in previous neuroimaging research (e.g., Morfardini et al., 2008, 2013). There were 2 binary S-R rules over four continuous learning blocks (i.e.,“Q” =click on the left side and “C” = click on the right side and “C” =click on the left side and “Q” = click on the right side). Each block started with a video clip slide that shows the other person performing S-R mappings, which lasted around 5s. The subsequent implementation stage began after the rule disappeared. During the implementation stage, participants were required to make a response by clicking on the left or the right side of the box separated by the midline. There were 2 stimuli per rule repeating 6 times in each block with no feedback given after a response was made. Stimuli were presented in pseudo-randomized order. The next stimulus was displayed on the screen once participants made a response (Figure.21).

Figure.21. The outline of the observational learning (OL) task. A. The 2 binary discrimination rules demonstrated in the GIF. B. Task structure, including 2 discrimination rules over 4 blocks with 2 stimuli per rule repeating 6 times.

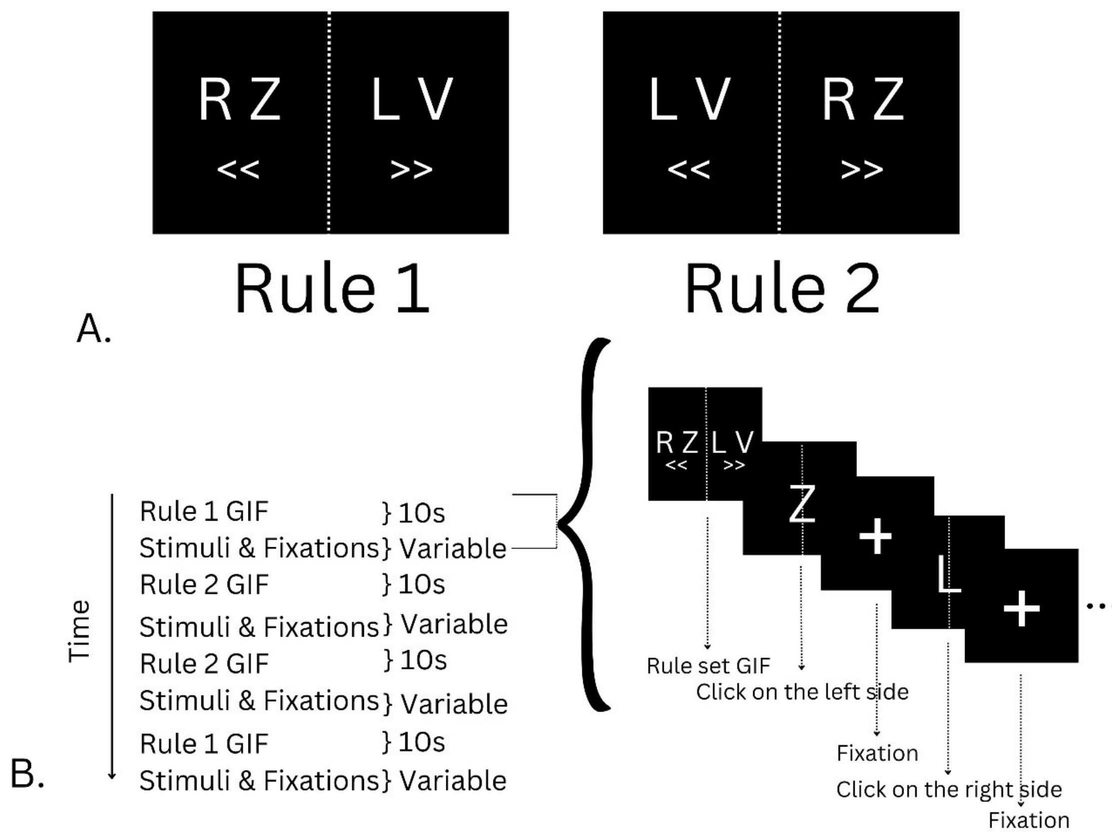


3.3.2.5. Complex observational learning (COL)

Specifically, participants were required to learn 4 binary S-R rules over four continuous learning blocks (i.e., “R” or “Z” = click on the left side and “L” or “V” = click on the right side and “L” or “V” = click on the left side and “R” or “Z” = click on the right side). Each block started with a slide that shows a premade video clip in GIF format regarding how another person is performing the task with two rules (e.g., “R” or “Z” = click on the left side and “L” or “V” = click on the right side), which lasted 10s. The subsequent implementation stage began after the rule disappeared. During the implementation stage, participants were required to make a response by clicking on the left or the right side of the box separated by the midline. There were

4 stimuli per rule repeating 3 times in each block with no feedback given after a response was made. Stimuli were presented in pseudo-randomized order. The next stimulus was displayed on the screen once participants made a response (Figure.22).

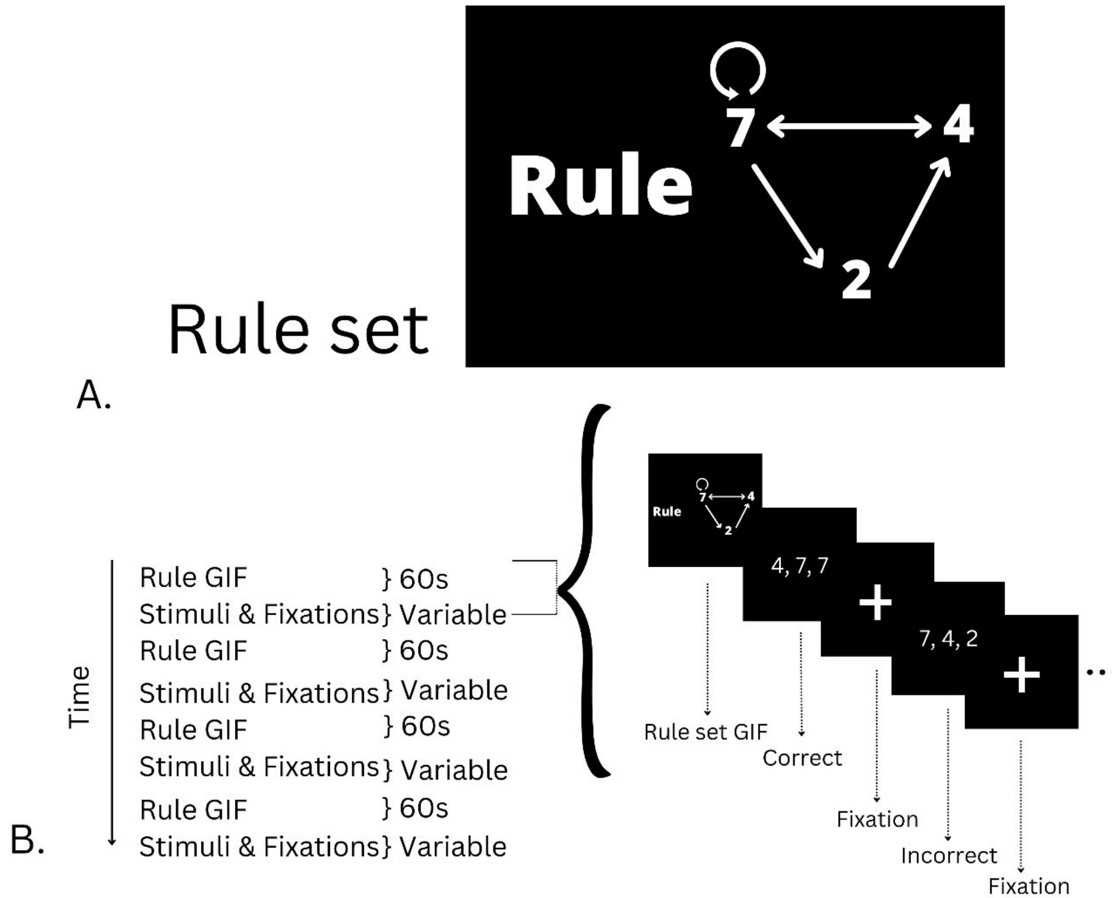
Figure.22. The outline of the complex observational learning (COL) task. A. The 2 quaternary discrimination rules demonstrated in the GIF. B. Task structure, including 4 discrimination rules over 4 blocks with 2 stimuli per rule repeating 3 times.



3.3.2.6. Model-based observational learning (MBOL)

The rule of the MBOL task was developed based on the artificial grammar task learning paradigm (Miller, 1958). However, participants learned artificial grammar by observation rather than instruction. Specifically, at the beginning of each block, participants were asked to view a premade video clip in GIF format regarding how another person is performing the task for 60s. During the implementation stage, participants were asked to determine if the pseudo-randomly combined digits ranging from 2 to 4 digits as "ruleful" (i.e., correct) or "unruleful" (i.e., incorrect). There were four blocks in total with 12 trails in each block. Stimuli were presented in pseudo-randomized order and each stimulus only appeared once. The next stimulus was displayed on the screen once participants made a response, and there was no feedback after a response was made (Figure.23).

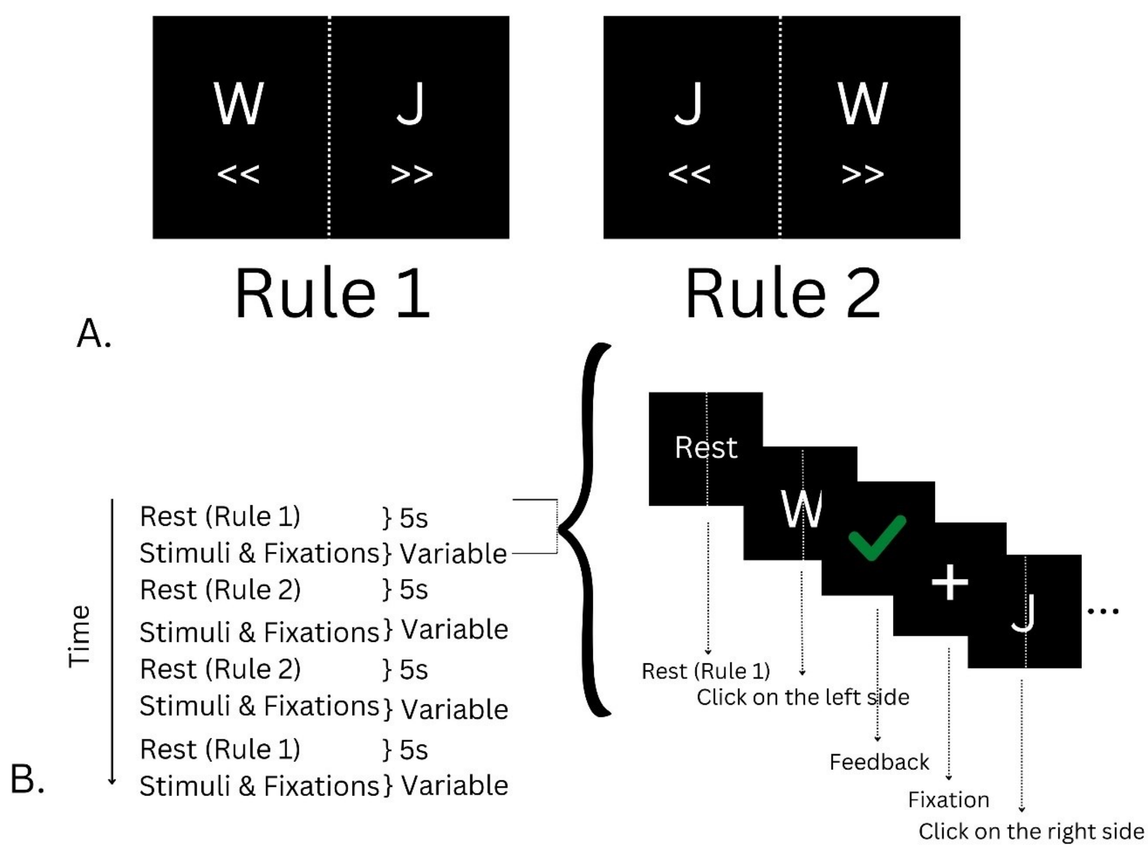
Figure.23. The outline of the model-based observational learning (MBOL) task. A. The model-based rule demonstrated in the GIF. B. Task structure, including one model-based rule over 4 blocks with 48 stimuli per block with no repeating.



3.3.2.7. Reinforcement learning (RL)

Similarly, the RL task was developed based on paradigms used in previous neuroimaging research on IBL (e.g., Hampshire et al., 2016). Specifically, participants were required to learn 2 binary S-R rules over 4 continuous learning blocks (i.e., “W” = click on the left side and “J” = click on the right side and “J” = click on the left side and “W” = click on the right side). There was no instruction phase in the RL. Instead, participants had to derive the rules themselves. Each block started with a slide that shows “rest,” which lasted 5s. During each block, participants were required to make a response by clicking on the left or the right side of the box separated by the midline. There were 2 stimuli per rule repeating 6 times in each block, and there was feedback with distinct sound for correct and incorrect response after a response was made to indicate if the response was correct or incorrect. Stimuli were presented in pseudo-randomized order. The next stimulus was displayed on the screen once participants received feedback for their response (Figure.24).

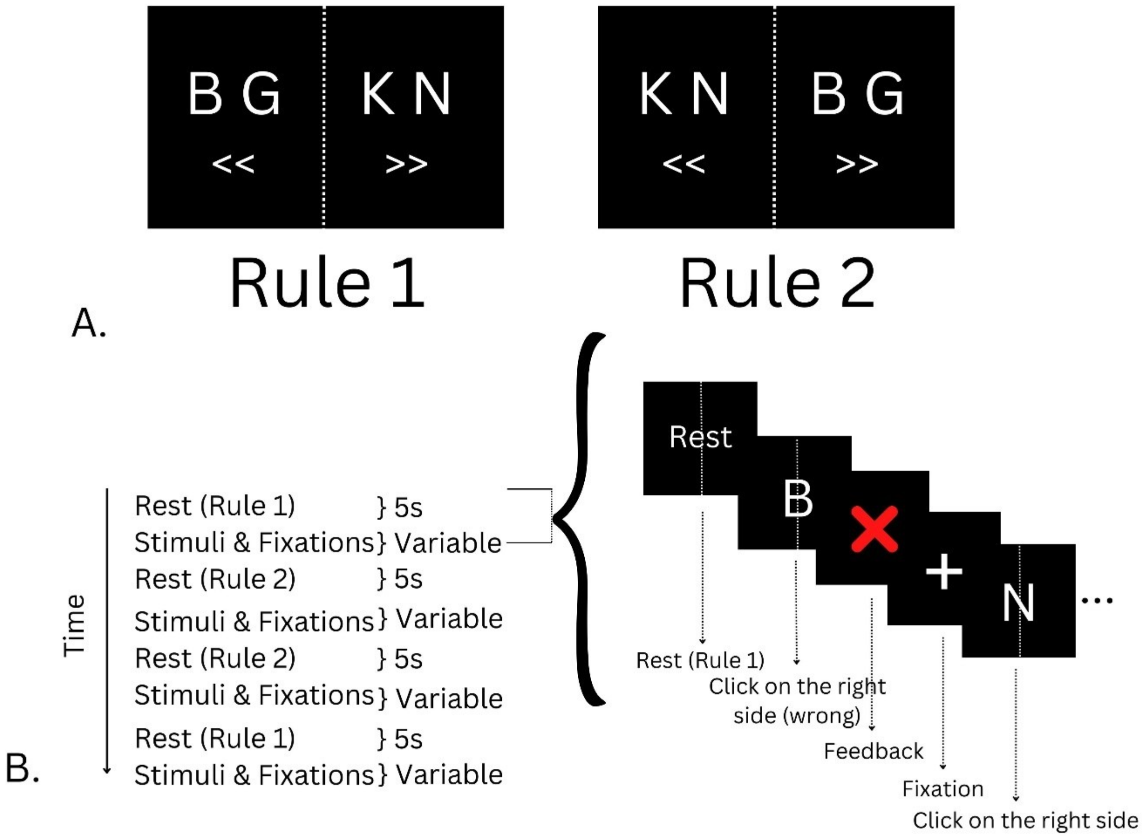
Figure.24. The outline of the reinforcement learning (RL) task. A. The 2 binary discrimination underlying rules. B. Task structure, including 2 discrimination rules over 4 blocks with 2 stimuli per rule repeating 6 times. The next stimulus was displayed on the screen once participants received feedback for their response.



3.3.2.8. Complex reinforcement learning (CRL)

Similarly, the CRL task has more S-R associations to learn. Specifically, participants were required to learn 4 binary S-R rules over four continuous learning blocks (i.e., “B” or “G” = click on the left side and “K” or “N” = click on the right side and “K” or “N” = click on the left side and “B” or “G” = click on the right side). There was no instruction phase in the RL. Instead, participants had to derive the rules themselves. Each block started with a slide that shows “rest,” which lasted 5s. During each block, participants were required to make a response by clicking on the left or the right side of the box separated by the midline. There were 4 stimuli per rule repeating 3 times in each trial, and there was feedback with distinct sound for correct and incorrect response after a response was made to indicate if the response was correct or incorrect. Stimuli were presented in pseudo-randomized order. The next stimulus was displayed on the screen once participants received feedback for their response (Figure.25)

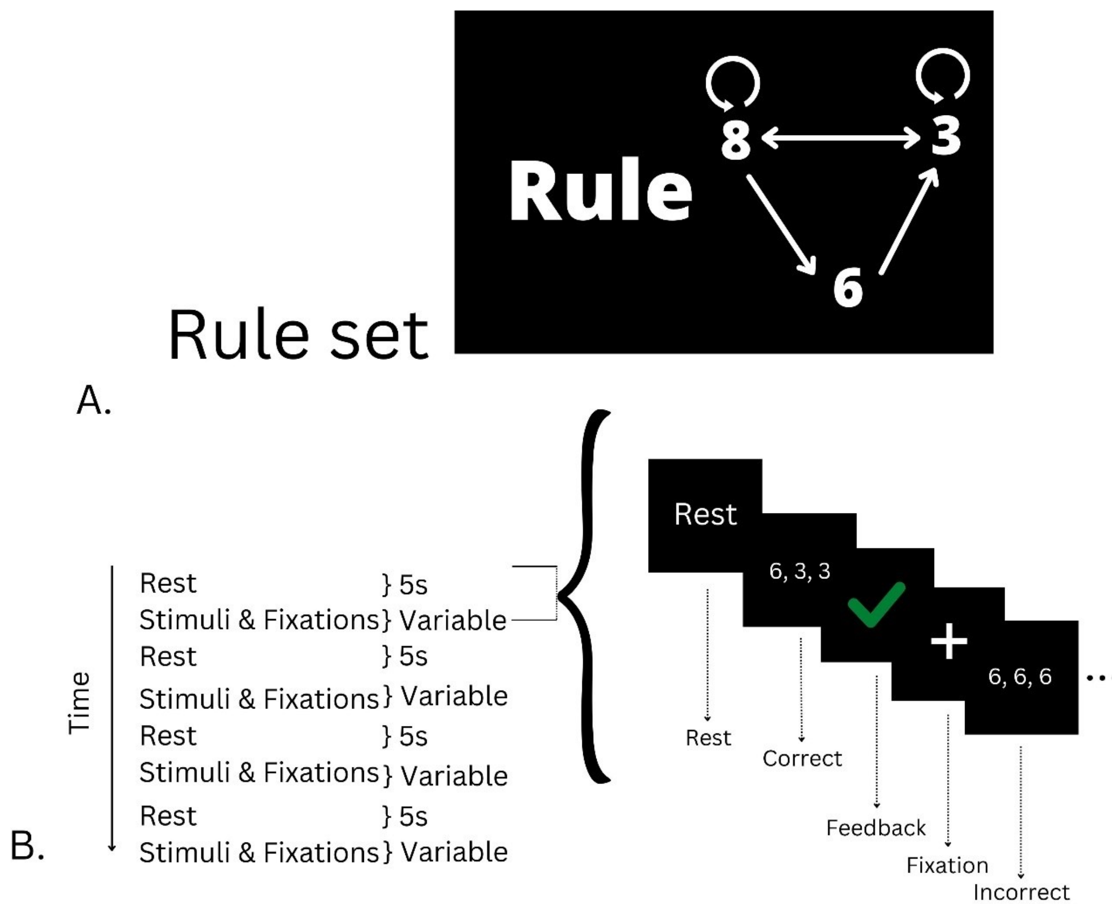
Figure.25. The outline of the complex reinforcement learning (CRL) task. A. The 2 quaternary underlying discrimination rules. B. Task structure, including 2 discrimination rules over 4 blocks with 2 stimuli per rule repeating 6 times. The next stimulus was displayed on the screen once participants received feedback.



3.3.2.9. Model-based reinforcement learning (MBRL)

The rule of the MBOL task was developed based on artificial grammar task learning paradigm (Miller, 1958). However, participants learned artificial grammar by trial-and-error rather than instruction. Each block started with a slide that shows “rest,” which lasted 5s. During each block, participants were asked to determine if the pseudo-randomly combined digits ranging from 2 to 4 digits as "ruleful" (i.e., correct) or "unruleful" (i.e., incorrect). There were 4 blocks in total with 12 trails in each block. Stimuli were presented in pseudo-randomized order. There was feedback with distinct sound for correct and incorrect response after a response was made to indicate if the response was correct or incorrect. The next stimulus was displayed on the screen once participants received feedback for their response (Figure.26)

Figure.26. The outline of the model-based observational learning (MBOL) task. A. The model-based underlying rule. B. Task structure, including one model-based rule over 4 blocks with 48 stimuli per rule with no repeating.



3.4. Analysis

The within-subject learning effect was analyzed using repeated-measures analysis of variance (RANOVA) by taking time*task*complexity as independent variable and learning performance as indicated by accuracy and RT for learning stage and block ad dependent variables respectively. Moreover, RANOVAs were also performance for each individual task as well by using learning stage and block to predict learning performance as measured by accuracy and RT respectively. The learning stage is defined as the within-block effect of learning whereas the learning block is defined as the cross-block effect of learning. Learning stages were further divided into four stages, the mean accuracy and RT for the first 3 trials averaged across blocks was defined as stage 1, the mean accuracy and RT for the second 3 trials averaged across blocks was defined as stage 2, the mean accuracy and RT for the third 3 trials averaged across blocks was defined as stage 3, the mean accuracy for the final 3 trials averaged across blocks was defined as stage 4. The mean accuracy and RT for the 12 trials of each block were defined as blocks 1, 2, 3, and 4 respectively.

I first performed an exploratory factor analysis (EFA) on the accuracy, RT, learning rate for accuracy and RT to understand the between-subject effect of learning. However, the EFA returned more or fewer components rather than 6 as we defined in the model. I also simulated data from 113 subjects by creating a 113*6 matrix with random values. Then I multiplied these values by a model constructed based on the learning type and complexity defined in our factorial design (i.e., [1 0 0 1 0 0; 0 1 0 1 0 0; 0 0 1 1 0 0; 1 0 0 0 1 0; 0 1 0 0 1 0; 0 0 1 0 1 0; 1 0 0 0 0 1; 0 1 0 0 0 1; 0 0 1 0 0 1]). Output from this procedure were then given a weight of 0.8 and were added together with noise (i.e., 113*9 matrix with randomly generated numbers) with a weight of 0.2. Finally, an EFA were performed but it turned 5 components rather than 6. All these pieces of evidence seem to suggest that factor analysis would not work well on the present factorial design. Then a confirmatory approach should be used. However, if using a confirmatory factor analysis (CFA) with 6 prespecified factors, the factor analysis did not work due to the collinearity issue.

Due to this, I used a permutation test instead to analyse the between-subject effect of intentional learning, which is a statistical hypothesis test that uses the proof by contradiction. Typically, there are two or more samples in a permutation test. The null hypothesis is that all samples come from the same distribution whereas the alternative hypothesis is that these samples come from a different distribution. The distribution of the test statistic can be then derived by calculating all possible values of the test statistics under possible rearrangements of the observed data. In the context of testing the between-subject effect of intentional learning, a permutation test can tell whether there's a significant difference between different groups of subjects (i.e., learning rates in different intentional learning tasks across three complexity levels). First, a model was constructed based on the learning type and complexity defined in my factorial design (i.e., [1 0 0 1 0 0; 0 1 0 1 0 0; 0 0 1 1 0 0; 1 0 0 0 1 0; 0 1 0 0 1 0; 0 0 1 0 1 0; 1 0 0 0 0 1; 0 1 0 0 0 1; 0 0 1 0 0 1]). Second, the latent variables from the model and observed data were estimated. Third, I re-estimated observations from the model and latent variables in order to calculate the residual variance. Fourth, the process was repeated but permuting the column labels 362, 880 times, which broke the linkage of tasks to the model. Finally, I evaluated the probability that the model of interrelationships between the tasks provides a better explanation of the data than other possible models of the same structural properties whilst maintaining the within-subject linkage of the data. This permutation test was applied to accuracy, RT, and learning rate for accuracy (the average slope across learning stages and learning blocks) and RT (the average slope across learning stages and learning blocks). All analyses were performed on MATLAB 2018a.

3.5. Results

The RANOVA showed that there is a significant stage*task*complexity interaction on accuracy ($F (24, 3{,}024) = 26.14$, $p < 0.001$) and RT ($F (24, 3{,}024) = 37.18$, $p < 0.001$). Similarly, there was a significant block*task*complexity interaction on accuracy ($F (24, 3{,}024) = 13.79$, $p < 0.001$) and RT ($F (24, 3{,}024) = 7.58$, $p < 0.001$).

Analysis of individual tasks showed that the main effect of stage and block on accuracy of the IBL and CIBL task was not significant. However, there was a significant main effect of stage ($F (3, 414) = 16.96$, $p < 0.001$) and block ($F (3, 414) = 89.70$, $p < 0.001$) on accuracy of the MBIBL task. There was a significant main effect of block ($F (3, 408) = 18.23$, $p < 0.001$) on the accuracy of the OL task. Similarly, there was a significant effect of stage ($F (3, 393) = 15.09$, $p < 0.001$) and block ($F (3, 393) = 18.23$, $p < 0.001$) on accuracy of the MBOL task. Finally, there was a significant effect of stage ($F (3, 432) = 151.03$, $p < 0.001$) and block ($F (3, 432) = 26.39$, $p < 0.001$) on accuracy of the RL task, a significant effect of stage ($F (3, 402) = 120.30$, $p < 0.001$) and block ($F (3, 402) = 17.56$, $p < 0.001$) on accuracy of the CRL task, and a significant effect of stage ($F (3, 417) = 12.02$, $p < 0.001$) and block ($F (3, 417) = 6.30$, $p < 0.001$) on accuracy of the MBRL task. These findings were visualised in Figure.27 and Figure.28.

There was a significant main effect of stage ($F(3, 429)=56.78$, $p<0.001$) and block ($F(3, 429)=7.04$, $p<0.001$) on RT of the IBL task. Similarly, there was a significant main effect of stage ($F(3, 435)=76.26$, $p<0.001$) and block ($F(3, 435)=8.92$, $p<0.001$) on RT of the CIBL task. As for the MBIBL task, I also found a significant main effect of stage ($F(3, 414)=199.41$, $p<0.001$) and block ($F(3, 414)= 35.51$, $p<0.001$) on RT. As for the OL, where was a significant main effect of stage ($F(3, 444)=73.78$, $p<0.001$) and block ($F(3, 444)=9.68$, $p<0.001$) on RT. Similarly, I found a significant main effect for stage ($F(3, 408)=29.17$, $p<0.001$) and block (F(3, 408)=18.21, $p<0.001$) on RT of the COL task. In addition, there was a significant main effect for stage ($F(3, 393)=66.58$, $p<0.001$) but not block on RT of the MBOL task. Finally, there was a significant main effect of stage ($F(3, 432)=218.53$, $p<0.001$) and block ($F(3, 432)=52.86$, $p<0.001$) on the RT of the RL task, stage ($F(3, 402)=91.41$, $p<0.001$) and block ($F(3, 402)=57.55$, $p<0.001$) on the CRL task, and stage ($F(3, 417)=66.23$, $p<0.001$) and block ($F(3, 417)=9.97$, $p<0.001$) on the MBRL task. These findings were visualised in Figure.27 and Figure.28.

Figure.27. The learning effect across stages for easy, complex and model-based instruction-based learning (IBL), observational learning (OL), and reinforcement learning (RL) as indicated by accuracy and reaction time (RT) respectively. The learning stage is defined as the within-block effect of learning. Learning stages are further divided into four stages, the mean accuracy and RT for the first 3 trials averaged across blocks was defined as stage 1, the mean accuracy and RT for the second 3 trials averaged across blocks was defined as stage 2, the mean accuracy and RT for the third 3 trials averaged across blocks was defined as stage 3, the mean accuracy for the final 3 trials averaged across blocks was defined as stage 4. Y axes = accuracy and RT in milliseconds (ms) respectively. RT is at different scales for easy and complex and model-based learning in order for learning to be clearly seen.

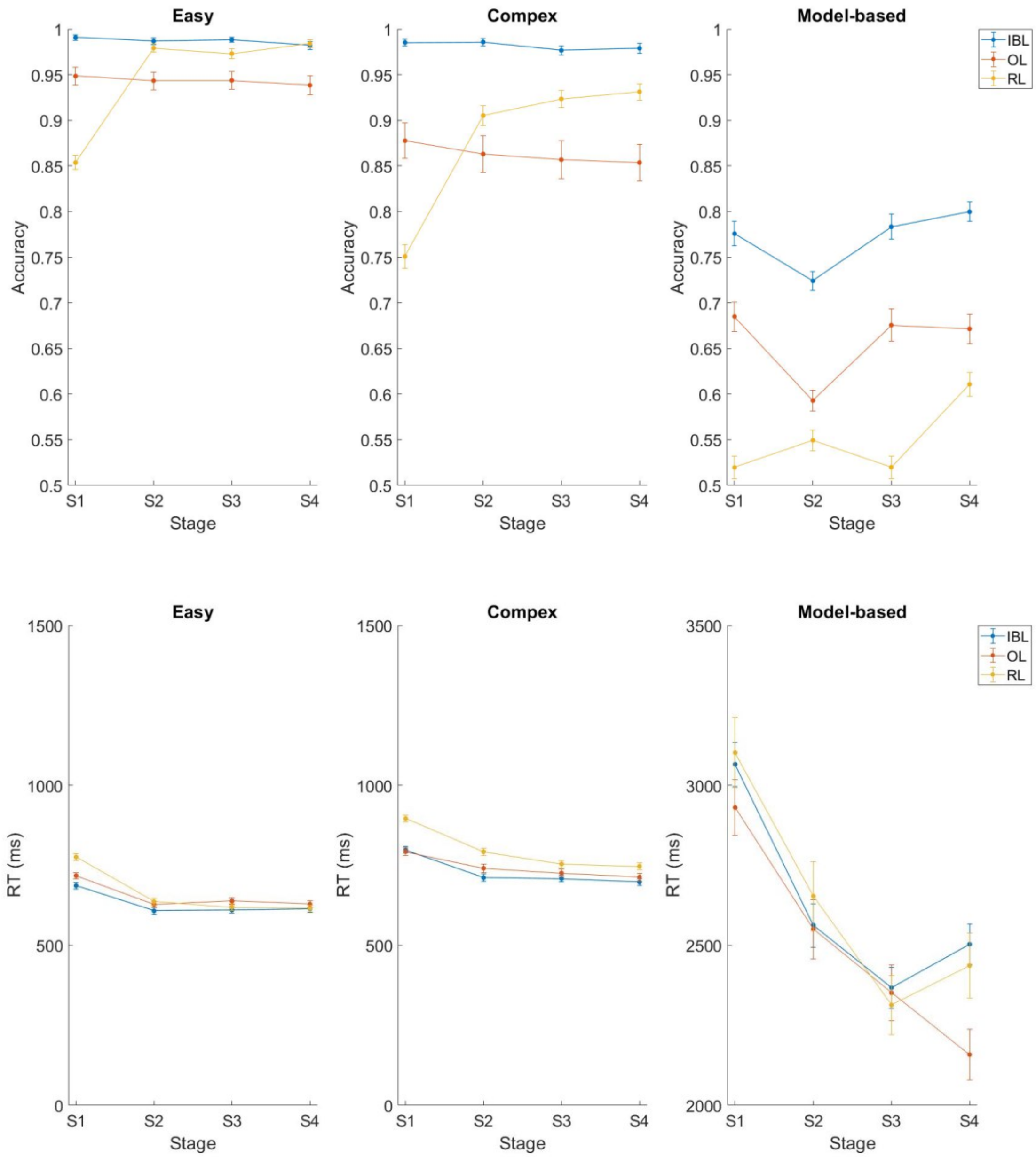
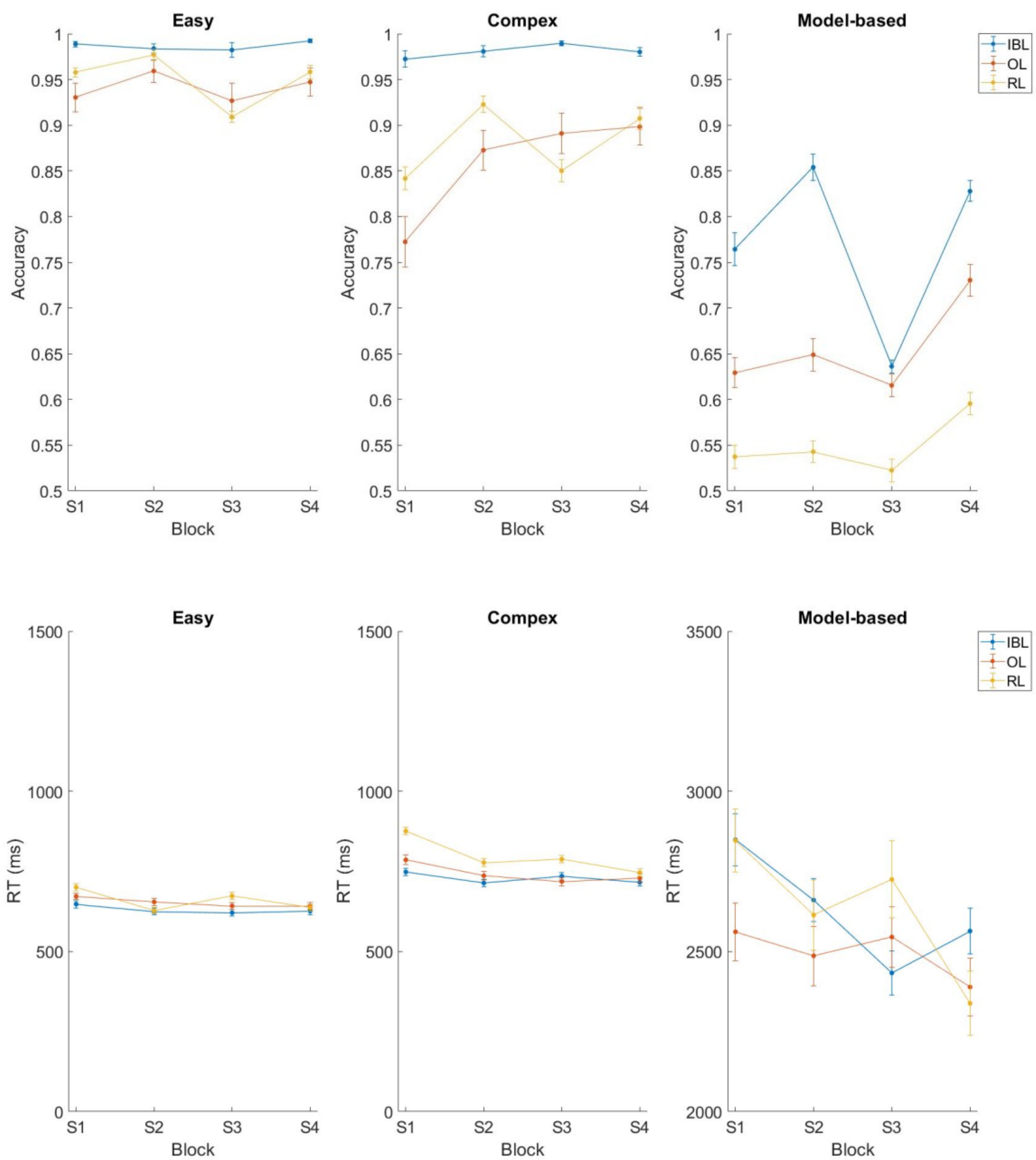


Figure.28. The learning effect across blocks for easy, complex and model-based instruction-based learning (IBL), observational learning (OL), and reinforcement learning (RL) as indicated by accuracy and reaction time (RT) respectively. The learning block is defined as the cross-block effect of learning. The mean accuracy and RT for the 12 trials of each block is defined as blocks 1, 2, 3, and 4 respectively. Y axes = accuracy and RT in milliseconds (ms) respectively. RT is at

different scales for easy and complex and model-based learning in order for learning to be clearly seen.



The permutation test showed the probability that the model of interrelationships between the tasks provides a better explanation of the data than other possible models of the same structural properties whilst maintaining the within-subject linkage of the data for accuracy

($p<0.05$), RT ($p<0.05$), and learning rate for RT across stages ($p<0.05$) and blocks ($p<0.05$) but not for learning rate for accuracy across stages ($p=0.09$) and blocks ($p=0.51$).

3.6. Discussion

The aim of the current study was to test the within and between- subject effect of various types of intentional learning including instruction-based learning (IBL; e.g., Cole et al., 2016; Hampshire et al., 2016, 2019; Ruge et al., 2019), reinforcement learning (RL; e.g., Daw et al., 2011; Gläscher et al., 2010), and observational learning (OL; Burke et al., 2010; Monfardini et al., 2008; 2013). By using RANOVAs and a permutation test, I found that (1) there is a clear within-subject learning effect across different tasks as indicated by increased accuracy but decreased RT with time, and (2) there is a between subject effect of intentional learning that can be explained by the type of intentional learning and the complexity of intentional learning as shown by the permutation test.

I developed nine computerized learning tasks based on the well-established literature, which include IBL (e.g., Cole et al., 2016; Hampshire et al., 2016, 2019; Ruge et al., 2019), OL (e.g., Burke et al., 2010; Monfardini et al., 2008, 2013), and RL (e.g., Daw et al., 2011; Gläscher et al., 2010). These different types of intentional learning are means to acquire S-R associations. Yet, how to achieve this goal differs by different types of intentional learning. Specifically, IBL requires the learner to acquire the S-R associations by comprehending the instruction, OL requires the learner to acquire the S-R associations by watching others, and RL requires the learner to try to figure out the rules by trail-and-error. In addition, I manipulated task complexity, which were two main established types of task complexity, namely the number of stimuli being included in one task and whether a task is model-based or model free. This resulted in three complexity levels for each learning task including simple, complex, and model-based.

Accuracy and RT are two important metrices to measure intentional learning. Specifically, accuracy reflects the extent to which an individual's could apply the learned S-R associations correctly whereas RT demonstrates how long it may take for one to make a response. One would expect accuracy to improve and RT to decrease over time if learning occurs (see De Houwer et al. (2013) for a review). Learning across stage and learning across blocks can be differentiated as well. Specifically, learning stage performance may reflect how fast people can acquire the S-R associations over a relatively short period of time, which is widely used in intentional earning research (e.g., Hampshire et al., 2016, 2019). On the other hand, the learning block performance is an important indicator of a more meta-level of learning, that is the improvements in performance over a relatively longer period of time.

The within-subject learning effect represents the variability of learning ability as measured by accuracy and RT within the same person across time. I analysed this within-subject learning effect using the repeated-measures analysis of variance (RANOVA), which revealed a significant stage*task*complexity interaction on accuracy and RT. Similarly, there was a significant block*task*complexity interaction on accuracy and RT. RANOVA on accuracy and RT for each individual learning tasks revealed that RT rather than accuracy showed the most significant effect of learning. Plotting these effects revealed improvement in performance as indicated by increased accuracy but decreased RT across stages and blocks (Figure.27, Figure.28), which seems to be consistent with the notion that learning results in an improvement in performance (see De Houwer et al. (2013) for a review). Specifically, participants were more and more accurate and fluent when performing these tasks as shown by increased accuracy but decreased RT over time through practice. Moreover, these learning curves were non-monotonic, which seems to be consistent with previous IBL research (Hampshire et al., 2016, 2019). In addition, the permutation test with a pre-specified model worked well for these different types of learning despite the levels of complexity, thus intentional learning is not a unitary ability per se. However, non-significant learning effects on accuracy were mainly observed in tasks with accuracy at the very early stage of learning, which may be explained by that participants did not have to learn much as they have already mastered the S-R association at the beginning so there is not much for them to learn.

Task complexity is another important factor that influences human behaviour and performance both in real-life scenarios and in the laboratory. I would expect that people tend to make more mistakes and react slower to more complex tasks compared to simple ones. Indeed, I found that there was a task*stage/block interaction. Indeed, as shown in Figure.27 and Figure.28, more complex tasks tend to have lower accuracy but higher RT than simpler ones. In this sentence, complex IBL/OL/RL are more complex than simple versions of these tasks given the more pairs of S-R associations to be memorized and executed. Model-based IBL/OL/RL is more complex than the complex and simple versions of these tasks.

The observed difference in learning types across various types of learning can be further explained by the different cognitive processes underlying these different learning abilities. Specifically, the commonality across these different types of learning includes identifying the goal of learning, attending to the stimuli, and encoding learned rules into working memory. However, the way in which a learner acquires rules differs. For example, in model-free RL, a learner learns by making responses and receiving feedback without such an internal model, whereas in model-based RL, a learner learns by making responses and receiving feedback with an internal model. In OL, one has to infer another's intention and then form a temporal program by integrating information from watching other's S-R associations whereas a learner forms a temporal program by comprehending the instruction in IBL.

A significant interaction according to the RANOVA for both accuracy and RT may indicate both the type of learning and complexity of learning matters. In order to further test if both task and complexity can explain a significant portion of variances in learning performance, a permutation test was used. The permutation test showed the probability that the model of interrelationships between the tasks provides a better explanation of the data than other possible models of the same structural properties whilst maintaining the within-subject linkage of the data for RT across stage and block respectively. Thus, the tasks I developed can well capture the type and complexity of learning as documented in the literature and prove that different people are in essence good at learning different things, and in different ways.

However, I did not find that the permutation test could account for the learning rate for accuracy across stages and blocks, which may be explained by the less obvious learning curves for accuracy as shown in Figure.27, which brings out the discussion of the caveats of this study. Perhaps there were very small differences in learning rate for accuracy across learning stages and learning blocks but successfully capturing them may need a larger sample size for detecting small differences. Another important limitation would be that the current study did not have demographic information, which may influence intentional learning performance in general. Other than demographics, psychiatric and neurological condition information should also be included in future studies given they may also affect the results.

Together, the current study provides an empirical understanding of "what" is being learned (complexity) and how it is being learned (type of intentional learning). These differences in the ability of learning can be attributed to the cognitive processes underlying different types of intentional learning and also the underpinning neural architectures. Thus, it is sensible for future studies to investigate (1) the different underlying cognitive processes in different types of intentional learning, and (2) the underlying neural architectures of different types of intentional learning across different levels of task complexity.

Chapter 4

Contribution of Cognitive and Personality Factors to Intentional Learning

4.1. Abstract

Chapter 3 developed a novel set of internet-based intentional learning tasks and validate their within-subject and latent variable properties. Results revealed that population variability in peoples' intentional learning performance can be explained differences in latent learning factors that align with "what" is being learned and "how" it is being learned. However, it remains unclear whether these different intentional learning profiles reflect more general cognitive abilities such as reasoning, attention and working memory, and personality traits, or should be considered distinct from either. Thus, the aim of Chapter 4 is to determine the degree to which cognitive abilities and personality traits can explain individual differences in intentional learning. I collected data for these tasks by emailing people who had participated in The Great British Intelligence Test. Among people who participated in my study, there were 420 participants who completed all personality inventories, cognitive tasks, and intentional learning tasks. I used canonical correlation, Pearson's correlation, and regression to analyse the data. I found that there is one significant mode in the relationship between personality and different types and complexities of learning and two significant modes in the associations between cognitive tasks and different learning tasks. However, these associations were rather week and may be explained by demographic characteristics. both personality and cognitive ability contribute to intentional learning, but that much of the population variability and differences in learning style cannot be explained by either; therefore, intentional learning may be considered largely divergent from either as a construct.

4.2. Introduction

Humans are able to learn new tasks rapidly via instruction, observation, and reinforcement. In addition, task complexity may play an important role in learning novel tasks. Specifically, there are several types of task complexity in the context of intentional learning, namely simple (i.e., fewer pairs of stimulus-response (S-R) associations to be encoded and executed), complex (i.e., more pairs of stimulus-response (S-R) associations to be encoded and executed), and model-based (i.e., learning with a model). One important metric that measures learning is learning rate, which is defined as the speed that participants acquire S-R associations. This is different learning tasks performance, which only measures how accurately/fast people could perform these learning tasks.

Personality traits, which refer to basic dispositional characteristics that capture individual differences in terms of how one perceives, thinks, and behaves. Among other personality models, the Big Five (i.e., Openness, Extraversion, Neuroticism, Agreeableness, and Conscientiousness) is one of the most widely used models, and other personality models can also be translated and conceptualized using the Big Five. In addition, compulsivity refers to the tendency towards urge-driven excessive and repetitive behaviour that is inconsistent with one's goals and tends to be associated with unfavorable consequences (Luigjes et al., 2019; Robbins et al., 2012). Rather than being considered as a psychopathology such as the obsessive-compulsive disorder (OCD), compulsivity can also be seen as a personality trait. The Cambridge–Chicago Compulsivity Trait Scale (CHI-T) is a recently developed inventory that can capture compulsivity with good psychometric properties (Chamberlain & Grant, 2018; Tiego et al., 2022). Moreover, studies generally agree that there are two underlying factors of the CHI-T, which include Perfectionisms (i.e., the need for completing tasks at a high standard) and Reward Drive (i.e., the tendency of acting on urges that are internally rewarding). While the Big Five personality traits can provide a broad framework for understanding personality, they may not directly measure compulsivity, although certain traits of the Big Five model are related to aspects of compulsivity. For instance, people who with a high score in Extraversion may be more prone to seeking out rewarding experiences that can lead to compulsive behavior, while someone high in Conscientiousness may be more inclined to engage in compulsive behaviors related to perfectionism.

Regarding the associations between personality traits and cognitive task performance, several hypotheses in the literature, which includes (1) there are no associations between personality and cognitive performance, (2) personality can influence cognitive performance, and (3) there might be a developmental relationship between personality and cognitive performance and personality may affect how much a person devotes to cognitive abilities and personality may inform cognitive performance in the long term (von Stumm et al., 2011). However, empirical evidence seems to favor the second and third hypotheses. Indeed, studies tend to find that Neuroticism is negatively related to cognitive tasks whereas other traits are positively related to cognitive performance (e.g., Chapman et al., 2017; Klaming et al., 2017) although there are some inconsistencies across studies. It is possible that Neuroticism contributes to cognitive performance through emotional pathways, however, there are inconsistent findings in the literature. For instance, Edwards et al. (2022) found that Neuroticism is not a predictor of cognitive performance after controlling anxiety and depression. However, one study has also found that Neuroticism is negatively related to altered information processing and learning, independent of the emotional content of the information (Byrom & Murphy, 2013).

Neurobiologically, personality traits may relate to cognitive tasks as personality is closely related to brain networks that support different types of cognitive task demands. Specifically, DeYoung et al., (2010) found that Neuroticism is associated with brain regions that are related to threat, punishment, and negative affect. Specifically, Neuroticism is negatively associated with dorsomedial PFC and in portions of the left medial temporal lobe, including posterior hippocampus, portions of basal ganglia and midbrain, including globus pallidus and bilateral subthalamic nuclei, and regions in the right precentral gyrus (De Young et al., 2010). In addition, brain regions that have associations with Neuroticism were found in bilaterally in mid-cingulate cortex, extending into the white matter of the cingulate gyrus and, in the left hemisphere, into the caudate as well as one region in the middle temporal gyrus and one in the cerebellum (De Young et al., 2010). Agreeableness is associated with the volume of brain regions that process information associated with others (e.g., the retrosplenial region of PCC, superior temporal sulcus, adjacent superior temporal gyrus, and fusiform gyrus). Conscientiousness is associated with the volume of the lateral prefrontal cortex, which is a brain region that is associated with planning and controlling behaviour (De Young et al., 2010). Extraversion is associated with the volume of the medial orbitofrontal cortex, which is a brain region involved in reward information processing (De Young et al., 2010). However, no association between Openness and brain volume was found. Omura et al. (2015) found that Neuroticism is negatively related to the gray matter volume of the right amygdala whereas Extraversion is positively associated with the gray matter volume of the left amygdala. Another study also found a significant relationship between Neuroticism and gray matter volume of the left amygdala (Koelsch et al., 2013). Gardini et al. (2009) found that Novelty Seeking (a facet of Extraversion; e.g., De Fruyt et al., 2000) is positively related to grey matter volumes in the cingulate cortex. Harm Avoidance (a facet of Neuroticism; e.g., De Fruyt et al., 2000) is negatively related to those of the orbitofrontal, occipital, and parietal cortices. Additionally, Reward Dependence (a facet of Extraversion; e.g., De Fruyt et al., 2000) is associated with a decreased value in the caudate nucleus. To summarise, although there are associations between personality traits and brain regions, there seem to be inconsistent findings across studies.

Thus, I hypothesise that Neuroticism is negatively related to learning rate whereas Openness, Extraversion, Agreeableness, Conscientiousness, Perfectionism, and Reward Drive are positively related to learning rate. In addition, Agreeableness may be particularly sensitive to observational learning where people need to process other's information whereas Extraversion could be closely related to reinforcement learning where reward information processing is needed.

The associations between compulsivity traits including Perfectionism (i.e., the tendency of completing tasks in the highest standard) and Reward Drive (i.e., the tendency to undertake works that are intrinsically rewarding) and learning are far less understood. Some indirect evidence came from research in people with obsessive-compulsive disorder (OCD). For instance, deficits in cognitive flexibility, memory, and goal-directed actions are found in adults with OCD (Abramovitch et al., 2013; Gillan et al., 2011; Purcell et al., 1998). Impaired goal-directed control is a hallmark of adult OCD (Gillan et al., 2011). In addition, Gottwald et al. (2018) found that adolescents with OCD have widespread learning and memory impairments. Although compulsivity traits do not equate to OCD, I hypothesise that people who score high in Perfectionism and Reward Drive tend to learn slower than people who score low in these traits. However, Reward Drive may be positively related to reinforcement learning because it is an intentional task mainly driven by reward.

As highlighted in Chapter 1, these forms of intentional learning involve several cognitive processes, which include spatial problem solving, spatial planning, working memory, spatial short-term memory, spatial visual attention, the ability to spatially manipulate objects in mind, semantic reasoning, the ability to identify the correct definitions of words, the ability to identify and discern between emotions, and inhibitory control. They may be related to learning task performance in two ways: (1) intentional learning requires different subprocesses that require these cognitive abilities, and (2) cognitive tasks and intentional learning tasks share similar neural networks, namely the multiple-demand network (Duncan, 2010; Hampshire et al., 2012, 2016, 2019). I hypothesise that the performance of all of these cognitive tasks is positively related to the speed that people learn S-R associations. In addition, reasoning abilities may be particularly sensitive to model-based learning abilities.

In sum, the associations between personality traits, cognitive task performance, and learning rate (defined as how fast individuals can acquire novel S-R associations) remain largely unexplored. Thus, I aim to investigate how different cognitive tasks and personality may relate to different types of intentional learning rate. There are three hypotheses: (1) Neuroticism is negatively related to learning rate whereas Openness, Extraversion, Agreeableness, Conscientiousness, Perfectionism, and Reward Drive are positively related to learning rate. In addition, Agreeableness may be particularly sensitive to observational learning (OL) where people need to process other's information whereas Extraversion could be closely related to reinforcement learning (RL) where reward information processing is needed. (2) People who score high in Perfectionism and Reward Drive tend to learn slower than people who score low in these traits. However, Reward Drive may be positively related to RL because it is an intentional task mainly driven by reward. (3) The performance of all of these cognitive tasks is positively related to the speed that people learn S-R associations. In addition, reasoning abilities measured may be particularly sensitive to model-based learning abilities.

4.3. Methods

4.3.1. Data collection

I collected the data from members of the general public, predominantly from the UK, who have participated in The Great British Intelligence Test, a collaborative citizen science project with BBC2 Horizon that launched in late December 2019, and who opted into being contacted about further studies. I recontacted them via email and asked them if they would like to participate in my learning studies. The data analyzed here include responses from August through September 2022. This study was approved by the Imperial College Research Ethics Committee (17IC4009). Participants provided informed consent via the study website prior to starting the assessment. Participants with any missing variables that I am interested in were removed from further analysis. Thus, there were 420 participants remaining for further analysis.

4.3.2. Instruments

4.3.2.1. The Big Five

The current study used the 18-item version of the "little" Big Five, which was developed and validated in Chapter 2. Specifically, participants answered questions that assess the five broad domains/traits including Openness, Extraversion, Neuroticism, Agreeableness, and Conscientiousness with a Likert scale ranging from 0 – 4 (0 = "*strongly disagree*", 1 = "*disagree*", 2 = "*neither agree nor disagree*", 3= "*agree*", 4 = "*strongly agree*").

4.3.2.2. Cambridge–Chicago Compulsivity Trait Scale (CHI-T)

The CHI-T is a 15-item self-report questionnaire that covers two broad aspects of compulsivity, namely Perfectionism and Reward Drive (Chamberlain & Grant, 2018; Tiego et al., 2022). An intermediate response option was added to the response scale ("*neither agree or disagree*") from the original validation study, such that participants responded 0 – 4 (0 = "*strongly disagree*", 1 = "*disagree*", 2 = "*neither agree nor disagree*", 3= "*agree*", 4 = "*strongly agree*").

4.3.2.3. Intentional learning tasks

Intentional learning tasks involve the simple version of instruction-based learning (IBL), observational learning (OL), and reinforcement learning (RL); the complex version of IBL, OL, and RL; and the model-based version of IBL, OL, and RL. These tasks are identical to those in Chapter 3. Two metrics were used to capture learning performance including learning performance and learning rate. Learning performance refers to mean accuracy and RT across the whole task. Learning rates were calculated by taking the average slope of the learning curve (Figure.27). Given that the learning curve is much more obvious according to RT compared to accuracy, we mainly focus on the learning effect and performance as indicated by RT. A larger RT in these tasks indicates poorer performance, whereas a small value in the negative range indicates a faster learning speed as RT decrease with practice.

4.3.2.4. Cognitive tasks

The cognitive tasks included in this study except for inhibitory control tasks are identical to those in Hampshire et al. (2021). Specifically, these nine tasks consist of 1. Block Rearrange, a test designed to measure spatial problem solving, 2. Tower of London, a task that measures spatial planning, 3. Digit Span, a test designed to assess working memory, 4. Spatial Span, a test to measure spatial short-term memory, 5. Target Detection, which measures spatial visual attention, 6. 2D Mental Rotations, a test designed to measure the ability to spatially manipulate objects in mind, 7. Analogical Reasoning, assessing semantic reasoning abilities. 8. Rare Word Definitions, measuring the ability to find the correct definitions of words, 9. Face Emotional Discrimination, a task that measures one's ability to differentiate emotions, and tasks that measure inhibitory control abilities including 10. Switching Stroop, 11. Bees, 12. Tic-Tac No, and 13. Stop Signal Task (SST). These tasks are robust across devices, sensitive to demographics including age, gender, and education level, manageable for older adults and patients with mild cognitive or motor deficits, and do not have strong correlation with each other. A larger RT in these tasks indicates poorer performance. However, the computer program did not record the RT of the Rare Word Definitions for most of the participants. Thus, accuracy rather than RT of rare word definition tasks was used in subsequent analysis.

4.3.2.5. Demographics

Demographics included age, gender (male vs. female), language (English vs. non-English), country of residence (UK vs. non-UK), ethnicity (white vs. non-white), education (degree vs. secondary), occupation (student vs. worker vs. retired vs. other), salary (N/A vs. 0-30 k vs. 30-60 k vs. 70-90 k vs. above 90 k), the number of hours that participants typically sleep per night, and the mood assessment factor score, which captures dimensions including depression, anxiety, insomnia, and tiredness (see supplementary material).

4.3.3. Statistical analysis

I used canonical correlation analysis (CCA) to confirm the latent variables related to intentional learning, which enables the examination to multivariate associations between personality traits and intentional learnings in a data-driven manner. The relationship between two sets of variables is referred to as canonical modes and the canonical correlation coefficient represents the strength of this relationship. Multivariate relationships can be inferred if there are any significant modes. Then back projections using Pearson's correlation can be used to determine the relative contribution of the two sets of variables to each mode. In the case of my study, I used two CCAs, the first two for personality and learning rate, and the other two for cognitive task performance and learning rate.

To understand how personality traits and cognitive task performance are associated with learning rate at a finer grain, we ran a Pearson's correlation based on personality, cognitive tasks, and RT of each learning task averaged across four stages.

In order to examine if demographic variables can explain the variances in the projections of personality traits, cognitive task performance, and learning rate, I used six generalized linear models by taking demographics including age, gender (male vs. female), language (English vs. non-English), country of residence (UK vs. non-UK), ethnicity (white vs. non-white), education (degree vs. secondary), occupation (student vs. worker vs. retired vs. other), salary (N/A vs. 0-30 k vs. 30-60 k vs. 70-90 k vs. above 90 k), the number of hours that participants typically sleep per night, and the mood assessment factor score as predictors and back projections for mode 1 for personality and learning rate, mode 1 for cognitive performance and learning rate, and mode 2 for cognitive performance learning rate as outcome variables respectively. All analyses were performed on MATLAB 2018a.

4.4. Results

CCA analysis revealed one significant mode ($p<0.01$) for personality traits vs. learning rate with a canonical coefficient value (r) of 0.32. Back projection of the canonical mode to personality traits and learning rates revealed a greater contribution of Openness ($r=-0.33$, $p<0.001$), Extraversion ($r=0.19$, $p<0.001$), Conscientiousness ($r=-0.71$, $p<0.001$), Perfectionism ($r=0.17$, $p<0.001$) and Reward Drive ($r=-0.54$, $p<0.001$) and a greater contribution of simple IBL ($r=-0.77$, $p<0.001$), complex IBL ($r=-0.10$, $p<0.05$), simple OL ($r=-0.05$, $p<0.001$), complex OL ($r=-0.45$, $p<0.001$), simple RL ($r=-0.68$, $p<0.001$), complex RL ($r=-0.56$, $p<0.001$), and model-based RL ($r=-0.17$, $p<0.001$) to the canonical mode (Figure.29). Pearson's correlation coefficients (r) of personality and RT for each task of all four stages were plotted in Figure.30.

Figure.29. Back projection of canonical variates to personality traits and learning task data from the canonical correlation analysis (CCA). Significant contributors of personality traits included Openness ($p<0.001$), Extraversion ($p<0.001$), Conscientiousness ($p<0.001$), Perfectionism ($p<0.001$) and Reward Drive ($p<0.001$). Significant contributions of intentional learning tasks included simple IBL ($p<0.001$), complex IBL ($p<0.05$), simple OL ($p<0.001$), complex OL ($p<0.001$), simple RL ($p<0.001$), complex RL ($p<0.001$), and model-based RL ($p<0.001$).
Y axes = Pearson's correlation coefficient (r).

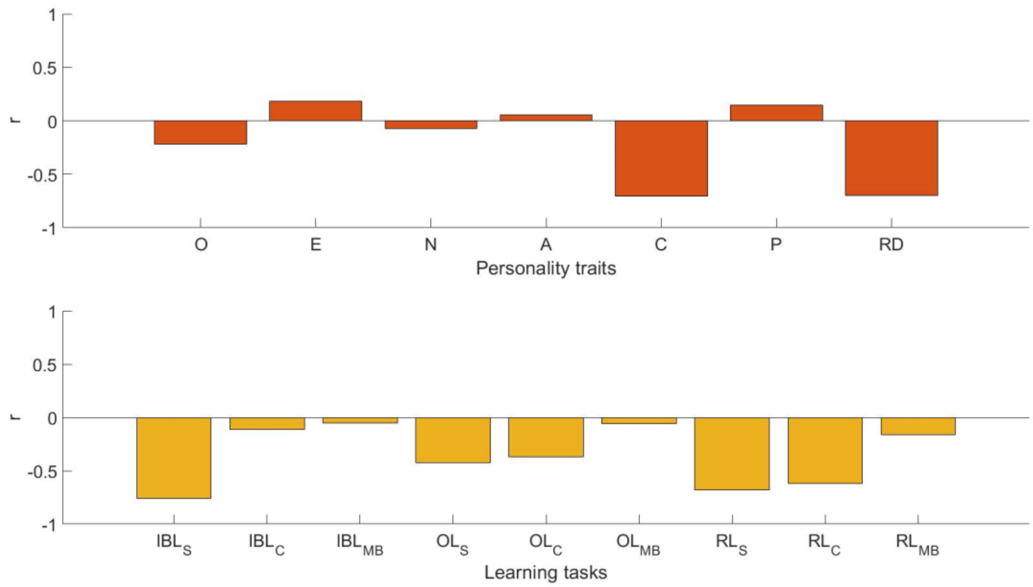
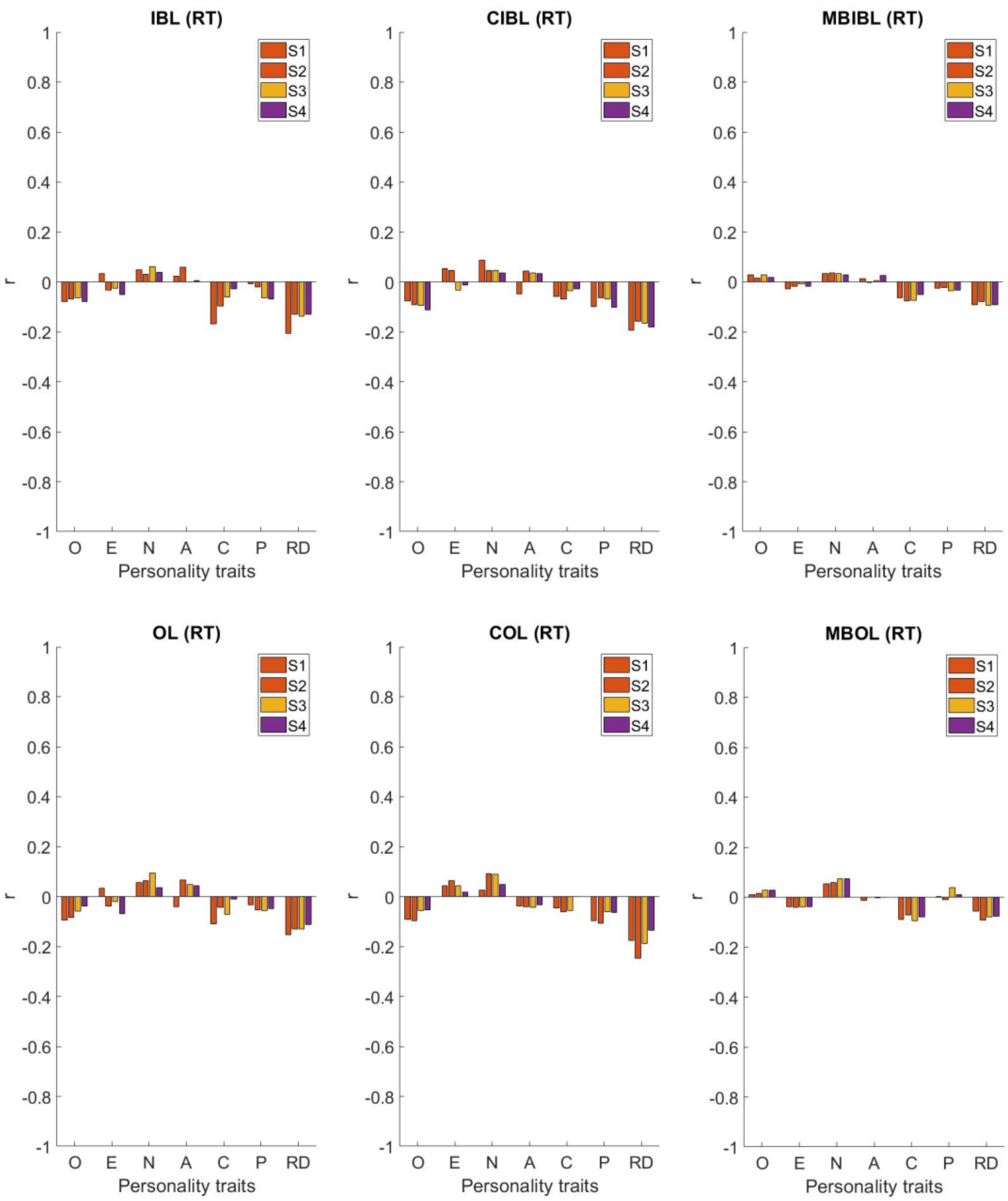
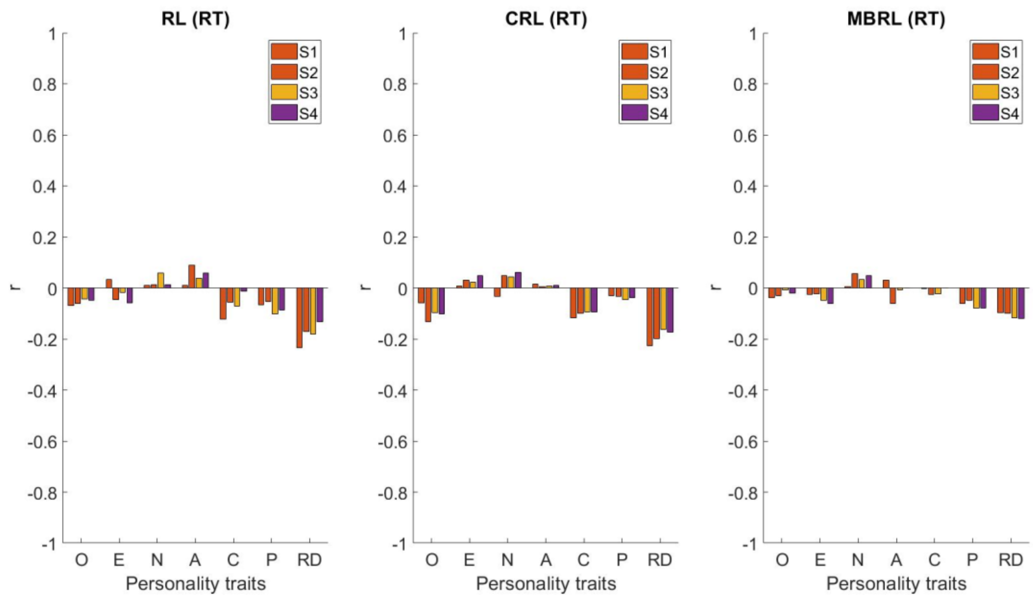


Figure.30. Pearson's correlation coefficients of personality and reaction time (RT) across four learning stages for different tasks. These were diverse patterns of correlations existing between personality and intentional learning tasks as indicated by both r and a threshold of $p<0.05$ as significant. However, the main trend is that these associations are strong at the first stage but gradually decrease with practice. Y axes = Pearson's correlation coefficient (r).



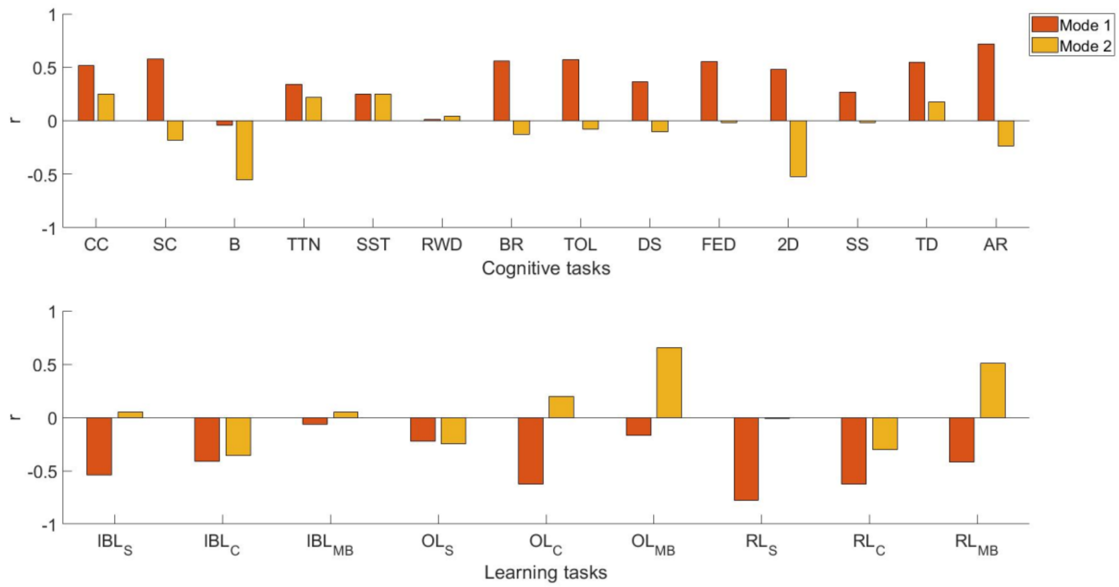
IBL (RT)
CIBL (RT)
MBIBL (RT)
OL (RT)
COL (RT)
MBOL (RT)
S1
S2
S3
S4
r
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
O
E
N
A
C
P
RD
Personality traits



The regression analysis using demographics as predictors to predict projections of personality traits and learning rate revealed that age ($F(1, 404)=27.84$, $p<0.001$; $b=0.02$, $p<0.001$) is positively related to the projection of learning rate whereas number of hour slept per day ($F(1, 404)=5.31$, $p<0.05$; $b=0.09$, $p<0.05$) and mood ($F(1, 404)=11.36$, $p<0.001$; $b=-0.17$, $p<0.001$) is negatively related to the projection of personality traits. In addition, secondary education ($F(1, 404)=7.42$, $p<0.01$; b (secondary)=0.28, $p<0.001$) was also positively related to the projection of learning rate.

Similarly, I found two significant modes ($p<0.001$ and $p<0.01$) for cognitive tasks vs. learning rate with canonical coefficient values (r) of 0.47 and 0.35 respectively. Back projection of the first canonical mode to cognitive scores and learning rates revealed a greater contribution of congruent cost of Switching Stroop ($r=-0.50$, $p<0.001$), switching cost of Switching Stroop ($r=-0.50$, $p<0.001$), stop-signal reaction time (SSRT) of the Tic-Tac No ($r=-0.31$, $p<0.001$) and the SST ($r=-0.23$, $p<0.001$), the RT of the Block Rearrange ($r=-0.53$, $p<0.001$), Tower of London (r=-0.55, p<0.001), Digital Span (r=-0.40, p<0.001), Face Emotion Discrimination (r=-0.57, p<0.001), 2D Mental Rotations (r=-0.49, p<0.001), Spatial Span (r=-0.25, p<0.001), Target Detection (r=-0.56, p<0.001), and Analogical Reasoning (r=-0.73, p<0.001) and a greater contribution of complex IBL (r=-0.35, p<0.001), model-based IBL (r=0.16 p<0.001), simple OL (r=-0.14, p<0.01), complex OL (r=0.17, p<0.001), model-based OL (r=0.63, p<0.001), complex RL (r=-0.40, p<0.001), and model-based RL (r=0.47, p<0.001) to the first canonical mode (Figure.31). Pearson's correlation coefficients (r) of personality and RT for each task of all four stages were plotted in Figure.32.

Figure.31. Back projection of canonical variates to cognitive task and learning task data from the canonical correlation analysis (CCA) for the two significant modes: mode 1 and mode 2. Significant contributors of cognitive tasks included congruent cost (cc) of Switching Stroop (p<0.001), switching cost (sc) of Switching Stroop (p<0.001), stop-signal reaction time (SSRT) of the Tic-Tac No (TTN, p<0.001) and the SST (p<0.001), the accuracy of rare word definition (RWD, p<0.05), the RT of the Block Rearrange (BR, p<0.001), 2D Mental Rotations (2D, p<0.001), Target Detection (TD, p<0.05), and Analogical Reasoning (AR, p<0.001). Significant contributions of intentional learning tasks included complex IBL (p<0.001), model-based IBL (p<0.01), simple OL (p<0.01), complex OL (p<0.001), model-based OL (p<0.001), complex RL (p<0.001), and model-based RL (p<0.001). Y axes = Pearson's correlation coefficient (r).

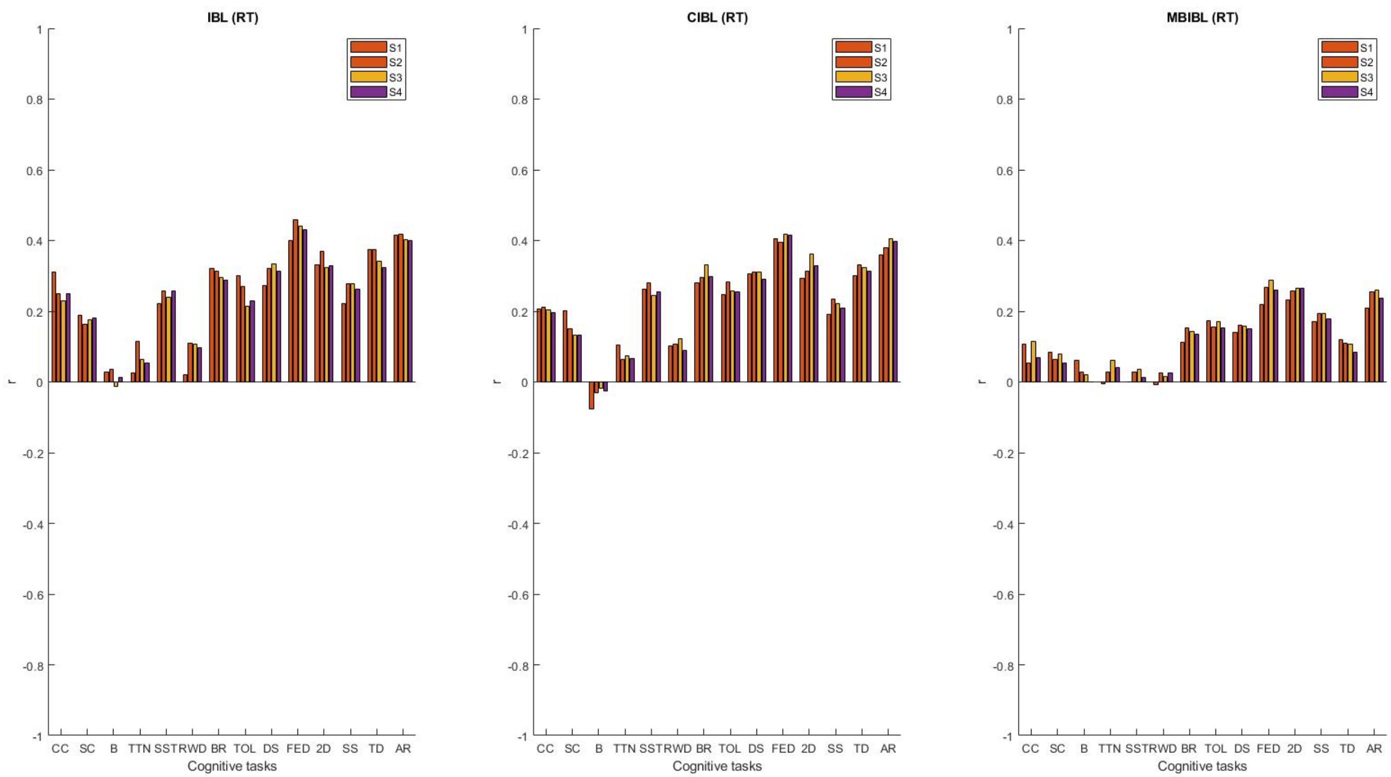


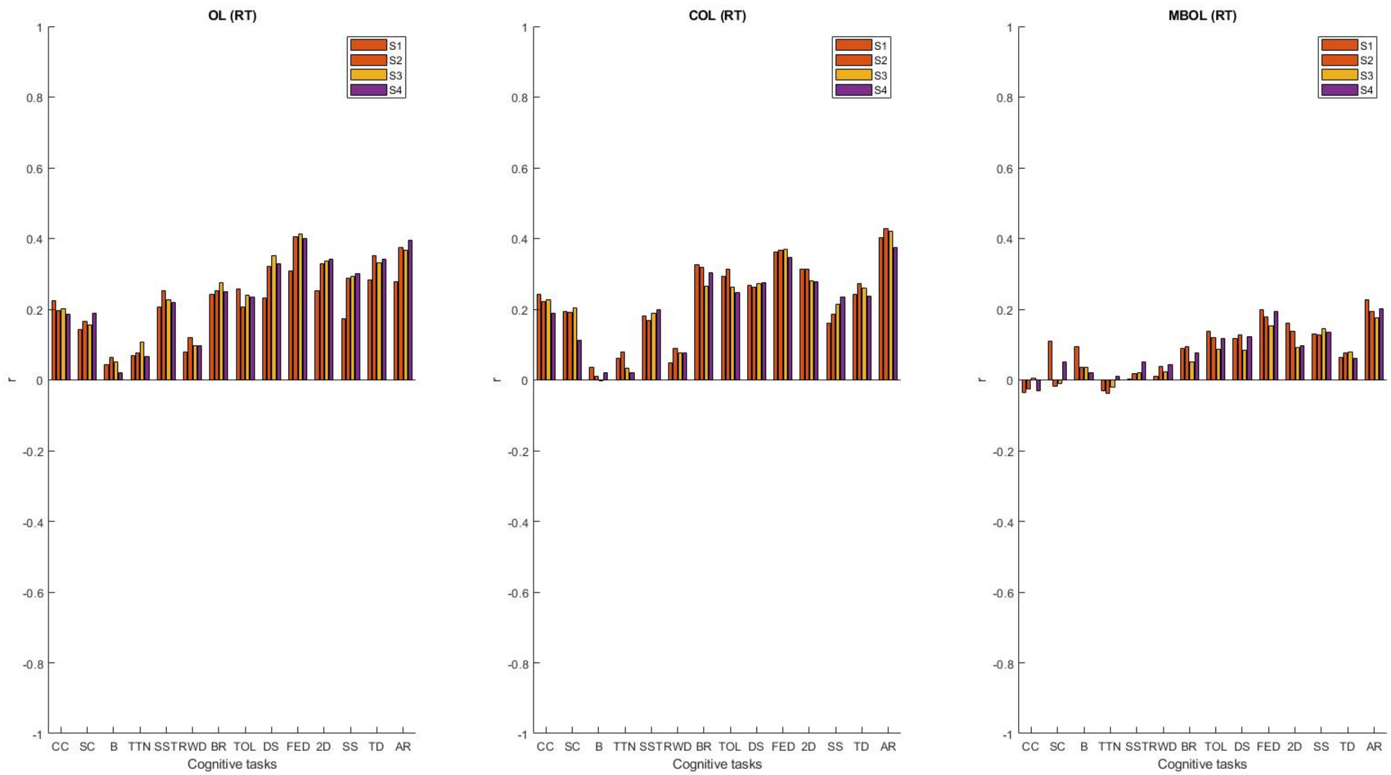
The regression showed that being a female (F(1, 404)=5.55, p<0.05; *b* (female)=0.22, p<0.05) and received secondary education (F(1, 404)=6.83, p<0.01; *b* (secondary)=0.26, p<0.01) are positively related to learning rate whereas secondary education (F(1, 404)=10.29, p<0.01; *b* (secondary)=0.28, p<0.01) was positively related to the first canonical projection of cognitive performance.

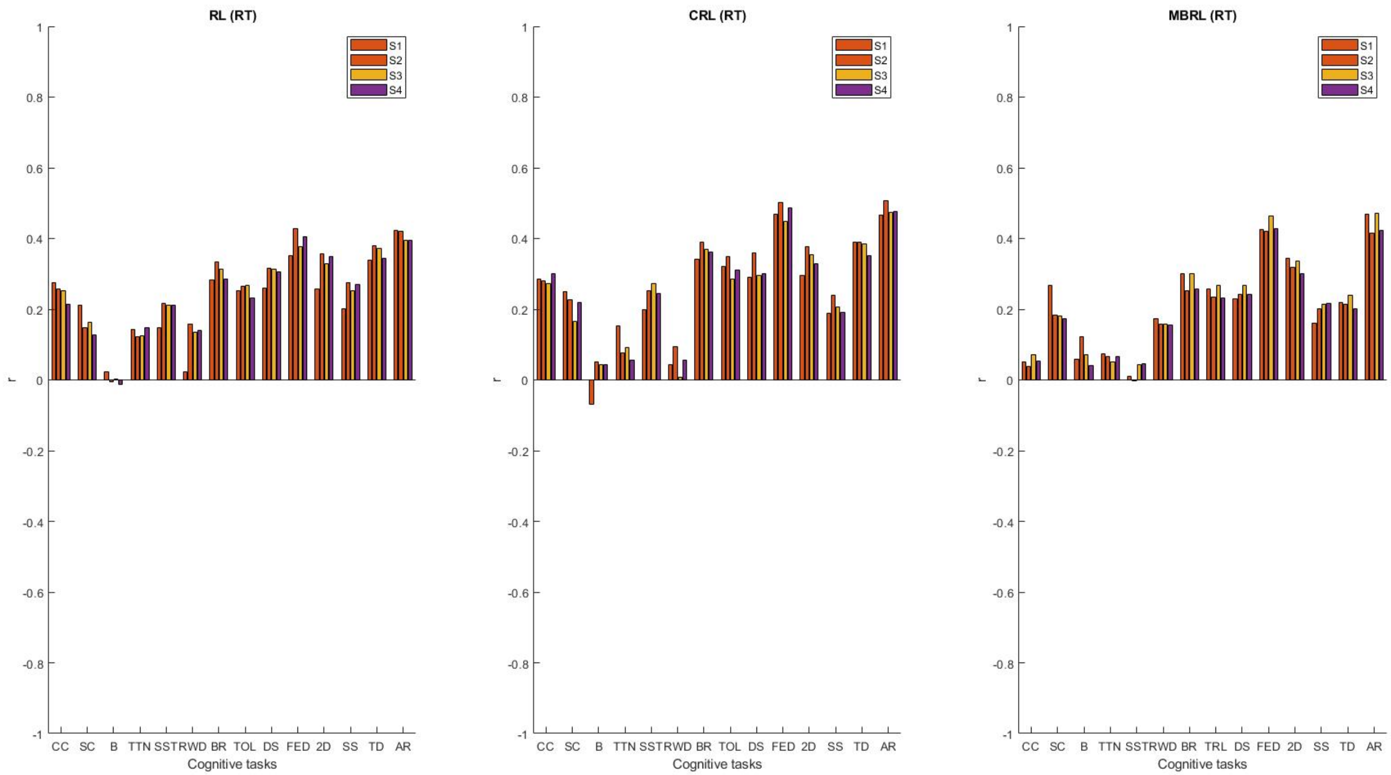
Back projection of the second canonical mode to cognitive scores and learning rates revealed a greater contribution of congruent cost of Switching Stroop (r=0.18, p<0.001), switching cost of Switching Stroop (r=0.25, p<0.001), means samples for the Bees task (r=-0.55, p<0.001), stop-signal reaction time (SSRT) of the Tic-Tac No (r=0.22, p<0.001) and the SST (r=0.25, p<0.001), the RT of the Block Rearrange (r=-0.13, p<0.001), Digital Span (r=-0.10, p<0.05), 2D Mental Rotations (r=-0.52, p<0.001), Target Detection (r=0.17, p<0.05), and Analogical Reasoning (r=-0.24, p<0.001) and a greater contribution of complex IBL (r=-0.36,

$p<0.001$), simple OL ($r=-0.24$, $p<0.001$), complex OL ($r=0.20$, $p<0.001$), model-based OL ($r=0.65$, $p<0.001$), complex RL ($r=-0.30$, $p<0.001$), and model-based RL ($r=0.51$, $p<0.001$). Pearson's correlation coefficients (r) of personality and RT for each task of all four stages were plotted in Figure.32.

Figure.32. Pearson's correlation coefficients of reaction time (RT) of cognitive tasks and RT across four learning stages for different tasks. These were diverse patterns of correlations existing between cognitive tasks and intentional learning tasks as indicated by r and a threshold of p<0.05 as significant. However, the main trend is that these associations are strong at the first stage but gradually decrease with practice. Y axes = Pearson's correlation coefficient (r).




OL (RT)
COL (RT)
MBOL (RT)
S1
S2
S3
S4
r
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
CC SC B TTN SSTRWD BR TOL DS FED 2D SS TD AR
Cognitive tasks


RL (RT)
CRL (RT)
MBRL (RT)
S1
S2
S3
S4
r
Cognitive tasks
CC SC B TTN SSTRWD BR TOL DS FED 2D SS TD AR
CC SC B TTN SSTRWD BR TRL DS FED 2D SS TD AR

In addition, the regression showed that having an income above 9,000 pounds ($F(4, 404)=2.47$, $p<0.05$; b (above 9,000 pounds)=-0.51, $p<0.05$) is negatively related to the second canonical projection of learning rate whereas having other race ($F(1, 404)=4.49$, $p<0.05$; b (other)=-0.49, $p<0.05$) was positively related to canonical projection of learning rate. Similarly, secondary education ($F(1, 404)=5.29$, $p<0.05$; b (secondary)=0.25, $p<0.01$) was positively related to the second projection of cognitive performance.

4.5. Discussion

This chapter aimed to understand the degree to which personality and cognitive abilities predict intentional learning. By using canonical correlation analysis (CCA) and Pearson's correlation, I found that there is one significant mode in the relationship between personality and different types and complexity of intentional learning and two significant modes in the associations between cognitive tasks and different intentional learning tasks. However, these associations were weak and diverse and may be explained by demographic characteristics, which may indicate that intentional learning is a distinctive set of constructs.

4.5.1. The relationships between personality and intentional learning

Back projection of the canonical mode between personality and intentional learning tasks revealed a greater contribution of Openness, Extraversion, Conscientiousness, Perfectionism, and Reward Drive. Specifically, Extraversion and Perfectionism were positively related to learning rate whereas Openness, Conscientiousness, and Reward Drive were associated with a slower learning rate. These findings were somewhat inconsistent with the original hypotheses given I hypothesised that Neuroticism is negatively related to learning rate whereas Openness, Extraversion, Agreeableness, Conscientiousness, Perfectionism, and Reward Drive are positively related to learning rate.

However, these results are still interpretable as Pearson's correlation analysis on the association between personality traits and RT of each learning stage suggested that these effects may be explained by the fact that people who score high in these traits tend to perform better on the first trials, as indicated by a smaller r, thus they do not need to acquire that much amount of information at a later stage. Thus, a negative correlation may not indicate that one has impaired learning ability, but rather it is an indication of a relatively strong ability to perform the task at the very beginning. On the other hand, a positive correlation may indicate the inability to achieve good results at the very beginning.

Neuroticism refers to the tendency of being emotionally unstable, which tends to have negative associations with cognitive abilities (Allen et al., 2019; Caselli et al., 2016; Hock et al., 2014; Luchetti et al., 2016). However, the present study failed to find any association between Neuroticism and intentional learning rates, which may be explained by that the effect of Neuroticism on learning rate is very small thus not well-detected due to my moderate sample size. In addition, Neuroticism tends to be associated with cognitive ability such as episodic memory in middle-aged or older people but not in older adults (Kang, 2023). It is certainly possible that this association in my sample may be significant in people in certain group (Kang, 2023), but this effect got cancelled out due to the diversity of age group included in the current study given age seems to be a significant factor in the projection of learning rate. Agreeableness refers to the tendency of being polite and easygoing. The finding that Agreeableness is unrelated to the learning rate is consistent with the notion that Agreeableness is generally unrelated to cognition (Kang, 2023).

Openness refers to the tendency to be open to new experiences. I found that Openness is associated with a slower learning rate, which can be explained by better performance at the very early stage of learning. This finding is consistent with the previous research that found the connections between Openness and cognitive abilities in general (Allen et al., 2019; Caselli et al., 2016; Hock et al., 2014; Luchetti et al., 2016; Sharp et al., 2010). Indeed, people who score high in Openness tend to participate in various cognitive stimulating activities such as cultural (Schwaba et al., 2018) and physical (Sutin et al., 2016) activities, which may then contribute to better performance at the early stage of learning and thus a slower learning rate.

Conscientiousness refers to the tendency of being task-focused and orderly, which is a personality trait that tends to be positively related to various cognitive abilities. The negative relationship between Conscientiousness and intentional learning rate generally agrees with previous studies on Conscientiousness and cognitive abilities. Conscientiousness has been linked to behaviours that can promote health, such as participating in physical activities (Kroenke et al., 2019; Sutin et al., 2016). However, Conscientiousness may lower risks of chronic disease (Weston et al., 2015), depression (Hakulinen et al., 2015), and weight gain (Jokela et al., 2013). Finally, Conscientiousness is associated with volume of the lateral prefrontal cortex, which is a brain region that is associated with various cognitive abilities (Hampshire et al., 2012) and intentional learning (Hampshire et al., 2016, 2019).

The results showed that reward drive is negatively related to learning rate, which is some expected but yet novel findings. Indeed, deficits in cognitive flexibility, memory, and goal-directed actions are found in adults with OCD (Abramovitch et al., 2013; Gillan et al., 2011; Purcell et al., 1998). Impaired goal-directed control is a hallmark of adult OCD (Gillan et al., 2011). In addition, Gottwald et al. (2018) found that adolescents with obsessive-compulsive disorder have widespread learning and memory impairments. Thus, people who score high in reward drive tend to learn slower.

Extraversion refers to the tendency of being outgoing and sociable. A positive association between Extraversion and learning rate is consistent with previous studies on Extraversion and cognition (e.g., Chapman et al., 2017; Klaming et al., 2017). Extraversion could contribute to learning via pathways that enhance memory such as more frequent social interaction (Stephan et al., 2014), better sleep quality (Stephan et al., 2018), and less stress (Leger et al., 2016). In addition, Extraversion is associated with the volume of the medial orbitofrontal cortex, which is a brain region involved in reward information processing (De Young et al., 2010). This association could then explain why Extraversion is associated with reinforcement learning.

Finally, I found Perfectionism is positively related to learning rate. Perhaps due to the fact people who score high in Perfectionism aim to complete the learning tasks with their highest standard, thus they did not respond fast as they were trying to respond as accurately as possible (Tiego et al., 2022). However, their RT tends to decrease once they feel confident that they have acquired these rules. This construct may be different from the trait that makes people who are at the higher risks of OCD, which could impair learning (e.g., Gottwald et al., 2018).

4.5.2. The relationships between cognitive performance and intentional learning

Similarly, the performance of most cognitive tasks including Switching Stroop, Tic-Tac No SST, Block Rearrange, Tower of London, Digital Span, Face Emotion Discrimination, 2D Mental Rotations, Spatial Span, Target Detection, and Analogical Reasoning were negatively related to learning rate, which means that people who have these abilities tend to learn slower in these tasks. Similarly, Pearson's correlation analysis on the association between the performance of different cognitive tasks and RT of each learning stage of learning revealed generally strong positive correlations between RT of different cognitive tasks and RT of different learning stages. For instance, previous studies have found that the MD system (Duncan, 2010), which refers to a set of frontal-parietal regions that are recruited across various cognitive tasks tends to be less active as people are getting more and more fluent at performing novel tasks. Thus, I hypothesised that different cognitive tasks are associated with a fast learning rate.

These results seem to be contradictory to the above-stated hypothesis, which speculated that people who have better cognitive abilities tend to learn fast in different types of intentional learning. However, findings from the current study are very interpretable as people who have higher cognitive abilities tend to perform better at the very start, as indicated by a small r value at the fist trials. As a result, they do not need to learn as much through practice. These findings are also consistent with the cognitive model I proposed in Chapter 1, attention, memory, and executive function are important abilities across different types of learning. In addition, the Face Emotion Discrimination task RT is also associated with different types of learning, which may be explained by the fact that the Face Emotion Discrimination task has a similar task structure to all intentional learning tasks I developed. Reasoning was hypothesised to be especially sensitive to model-based learning, but the fact was that reasoning is closely related to most types of learning, which may highlight that all types of learning require one's ability to make inferences about the S-R rules. From a cognitive neuroscience point of view, these cognitive tasks may share the same underlying brain systems such as the multiple-demand (MD) network with different types of learning.

Consistent with my hypothesis, the second canonical mode found that reasoning abilities as measured by 2D Mental Rotations, Analytical Reasoning, and Block Rearrange are related to a slower learning rate, and intentional learning rate canonical variates loaded heavily on model-based OL and model-based RL, which indicate that people who are better at reasoning tend to learn slower. These findings can then be explained by better first-trail performance as indicated by a small r value in the first few trails in these intentional learning tasks among people who have better reasoning abilities.

4.5.3. Potential demographic factors in explaining the associations between personality traits, cognitive performance

In addition, age and education are related to the projection of learning rate whereas number of hours slept per day and mood are related to the projection of personality traits in the only canonical mode existed between personality traits and learning rate. Gender and education were significant contributors to learning rate whereas education was a signification contributor of cognitive performance in the first canonical mode between cognitive performance and learning rate. Finally, race was a significant contributor to learning rate whereas education was a signification contributor of cognitive performance. In addition, income contributed to the second canonical projection of learning rate whereas race contributed to canonical projection of learning rate. Similarly, education was related to the second projection of cognitive performance.

These results may suggest that demographic characteristics may play a role in the associations between personality, cognitive performance, and intentional learning rate. However, future studies are needed to further clarify the interrelations between them.

4.5.4. Limitations

Despite its strength, there are some limitations of my study as well. First, I did not collect information regarding whether one has a neurological condition, which may make it impossible to rule out the potential effect of neurological impairments. Second, it is important to be cautious in inferring neurological or psychological inferences without neuroimaging data, although most of the cognitive tasks used in the study can be mapped to the corresponding networks in healthy individuals as well as in people with structural network damages (Hampshire et al., 2012; Jolly et al., 2020; Soreq et al., 2021). Finally, given this study is cross-sectional, limitations pertaining to cause and effect should be considered (Ellul et al., 2020; Holmes et al., 2020).

4.5.5. Conclusions

Taken together, I analysed how personality traits captured by the Big Five inventory and the CHIT and different cognitive abilities including spatial problem solving, spatial planning, working memory, spatial short-term memory, spatial visual attention, the ability to spatially manipulate objects in mind, semantic reasoning, the ability to identify the correct definitions of words, the ability to identify and discern between emotions, and inhibitory control are related to different types of intentional learning at various levels of complexity. Findings revealed that there was one significant mode in the relationship between personality and different types and complexities of intentional learning and two significant modes in the associations between cognitive tasks and different learning tasks. Demographic characteristics may play a role in their associations.

The relationships between personality, cognitive performance, and intentional learning are small and diverse for different types (i.e., instruction-based, observational, and model-based) of intentional learning at three complexity levels (i.e., simple, complex, and model-based) and demographics may explain their associations, these results may indicate that personality or cognitive performance alone could not well taken intentional learning into account. Thus, intentional learning should be considered as a distinctive set of constructs.

4.6. Supplementary material

Table.1. Demographic information of the participants.

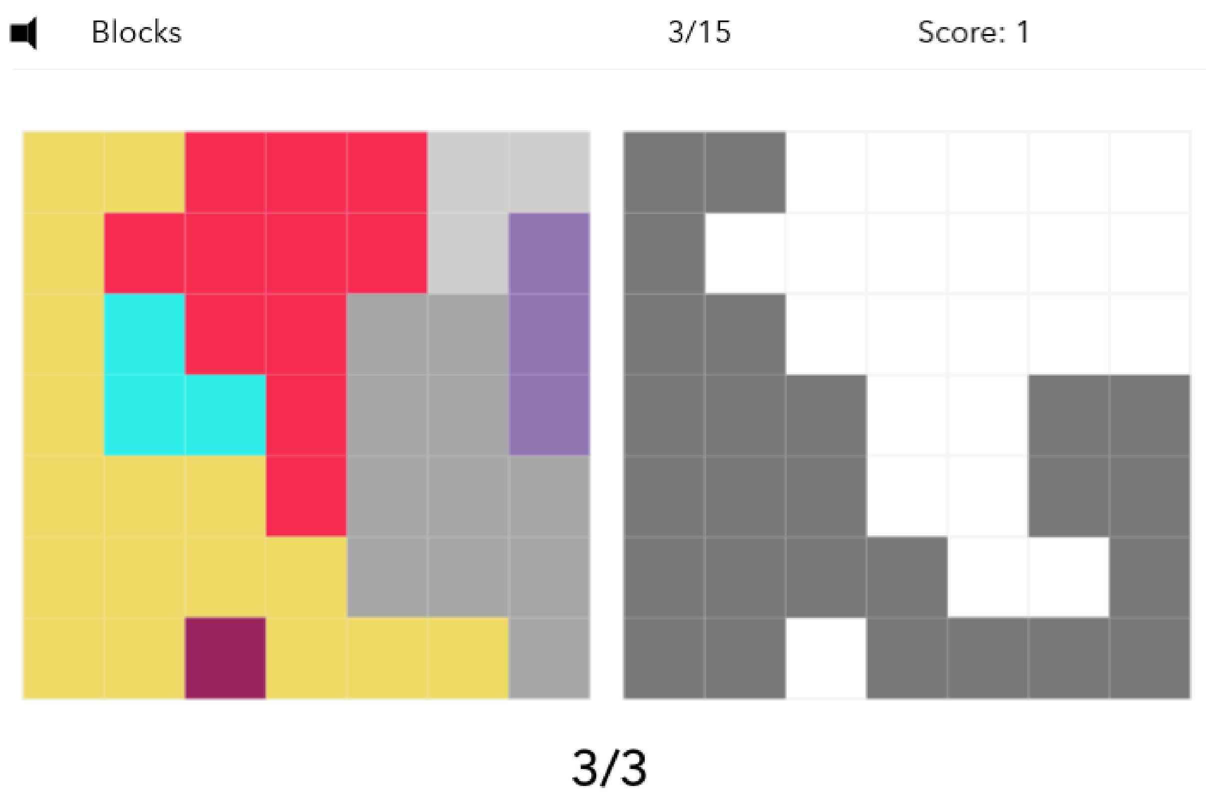
Variables	Mean	S.D.
Age	50.92	15.10
Number of hours sleep per night	7.08	1.29
Mood assessment score	-0.09	1.04
	Count	%
Gender		
Male	184	43.81
Female	236	56.19
Language		
English	396	94.29
Other	24	5.71
Ethnicity		
White European or North American	397	94.52
Other	23	5.48
Country		
United Kingdom	393	93.57
Other	27	6.43
Education		
University degree	289	68.81
Secondary school/High school diploma	131	31.19
Income		
£0-30K	98	23.33
£30-60K	84	20.00
£70-90K	29	6.90
>90K	22	5.24
Prefer not to say	187	44.52
Occupation		
Worker	244	58.10
Retired	118	28.10
Student	26	6.19
Other	32	7.62

Table.2. Mood self-assessment items.

Over the last two weeks, how often have you been bothered by the following problems? Responses: Never; Almost Never; Once or Twice Per Week; Several Times Per Week; Daily; Hourly; More Often.
Q1. Feeling nervous, anxious or on edge
Q2. Not being able to stop or control worrying
Q3. Worrying too much about different things
Q4. Trouble relaxing
Q5. Being so restless that it is hard to sit still

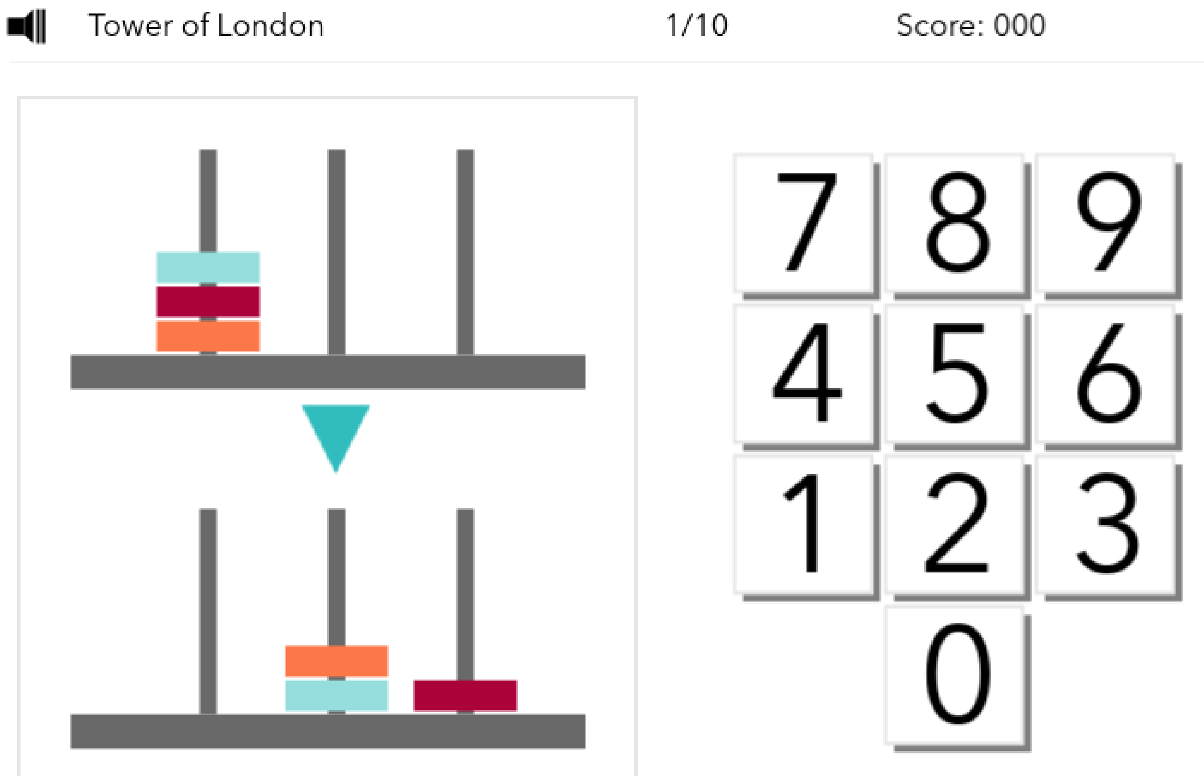
Q6. Becoming easily annoyed or irritable
Q7. Feeling afraid as if something awful might happen
Q8. Little interest or pleasure in doing things
Q9. Feeling down, depressed, or hopeless
Q10. Feeling tired or having little energy
Q11. Trouble concentrating on things such as reading the newspaper or watching television
Q12. Not being able to get to sleep or stay asleep

Task descriptions adapted from Hampshire et al. (2021) supplementary material.
Block Rearrange
The Block Rearrange test measures spatial problem solving. The participant is presented with a grid of coloured blocks on the left-hand side of the screen and on the right-hand side, a black silhouette made up of a subset of the shapes on the left. The participant must make the shape of the left-hand blocks match the silhouette on the right-hand side by removing blocks. The blocks fall under gravity. The test comprises 15 trials of varying difficulty. The difficulty is modulated by two factors; the number of blocks needed to remove and the number of blocks that must fall in order to reach the target silhouette. Each trial is terminated if, either the target silhouette is reached (correct trial) or an incorrect block is removed (incorrect trial). The outcome measure is the total number of correct trials.



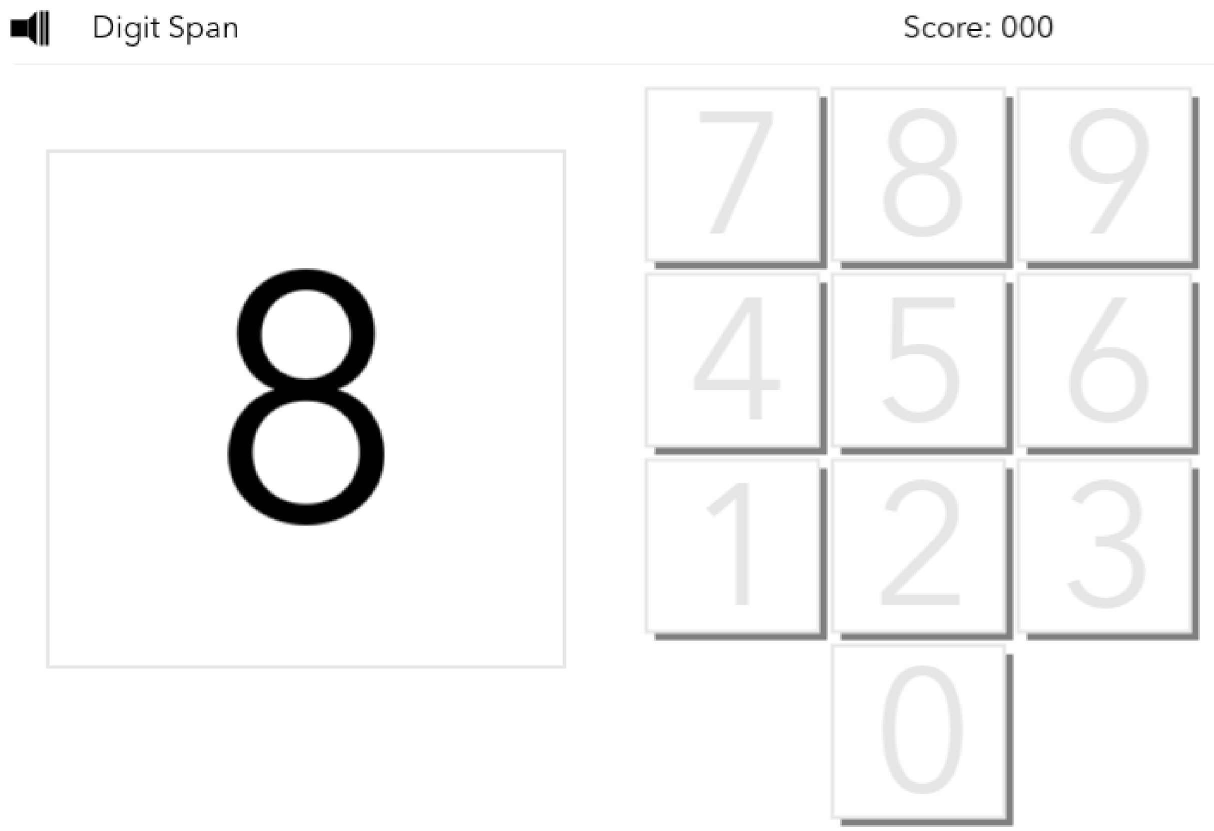
Tower of London
The Tower of London test measures spatial planning. It is a variant on the original Tower of London Test (Shallice, 1982). The participant is shown two sets of three prongs with coloured beads on them. The first set is the initial state and the second set is the target state. The participant must work out the lowest number of moves it would take to transition from the initial state to the target state. They must then input this number using an on-screen number pad. This differs from the original test in that the participant is not allowed to move the beads, all calculation and planning must be done in their head. This is to prevent correct answers being reached through iterative error correction. The test consists of 10 trials of variable difficulty. The

difficulty is scaled using the number of beads and the convolutedness, defined as the number of moves that must be made that do not place a bead in its final target position. The outcome measure is the total number of correct trials.

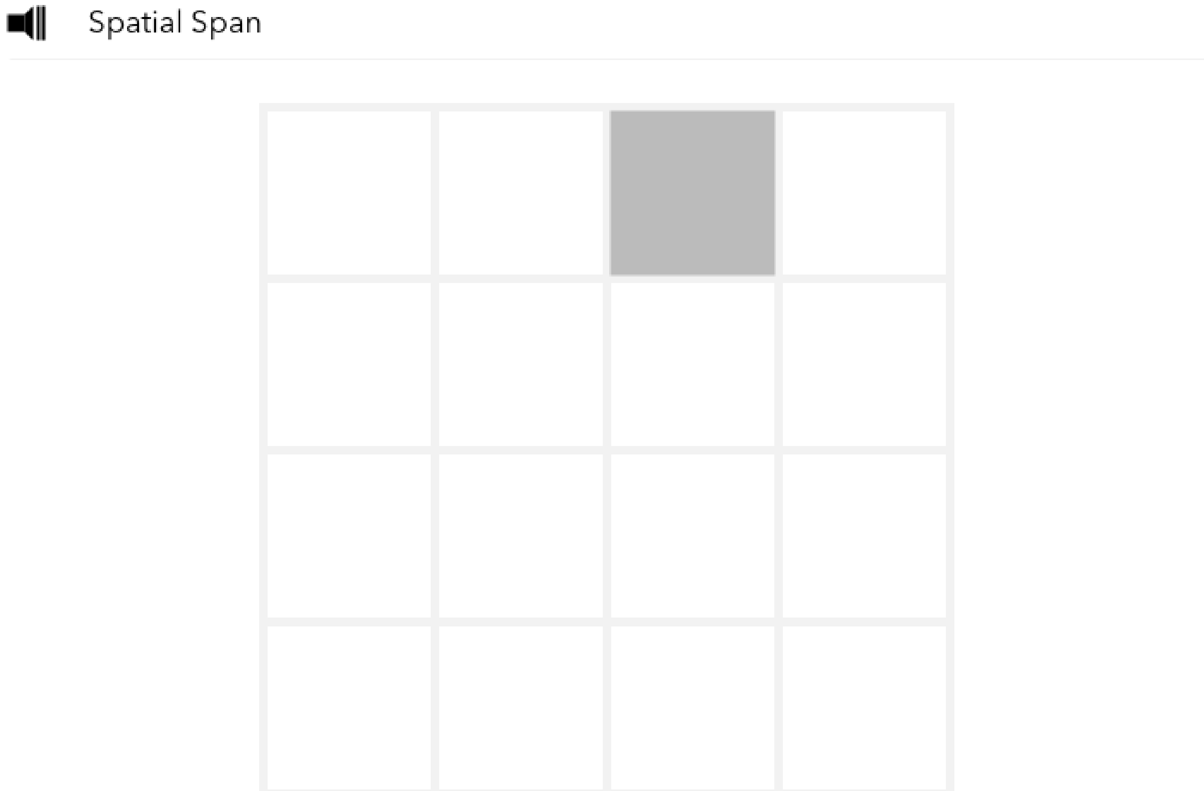


Digit Span

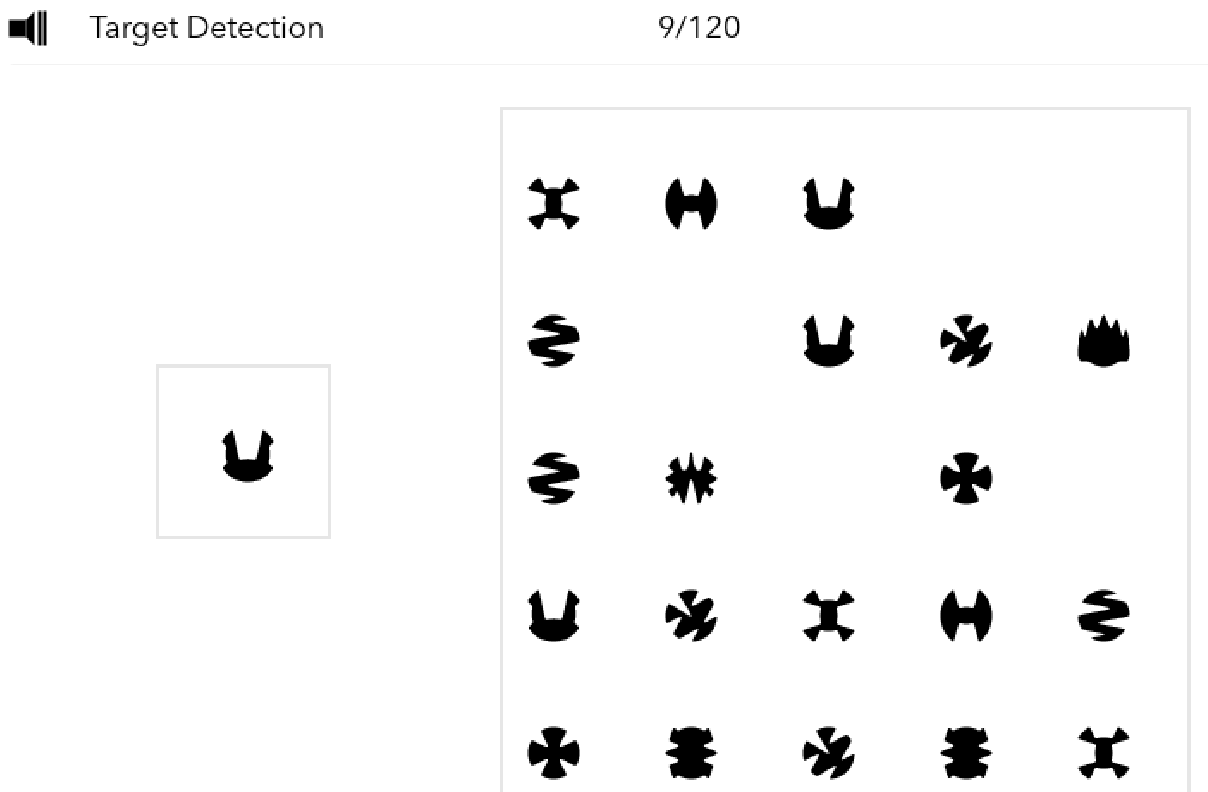
Digit Span is a computerised variant on the verbal working memory component of the WAIS-R intelligence test (Weschler, 1981). Participants view a sequence of digits that appear on the screen one after another. Subsequently, they repeat the sequence of numbers by entering them using an on-screen number pad. The difficulty is incremented using a ratchet system, every time a sequence is recalled correctly, the length of the subsequent sequence is incremented by one. The test is terminated when three consecutive mistakes are made on a particular sequence length. The outcome measure is the maximum sequence length correctly recalled. Minimum level = 2, maximum level = 20, ISI = 0ms, encoding time = 1000ms.



Spatial Span
The Spatial Span test measures spatial short-term memory capacity. It is a variant on the classic Corsi Block Tapping Test (Corsi, 1972). The participant is presented with a 4 x 4 grid, onto which is displayed a sequence of squares in different positions in the grid. The participant must then click the squares in the order that they were highlighted. The difficulty is incremented using a ratchet system, every time a sequence is recalled correctly, the length of the subsequent sequence is incremented by one. The test is terminated when three consecutive mistakes are made on a particular sequence length. The outcome measure is the maximum sequence length correctly recalled. Minimum level = 2, maximum level = 16, ISI = 0ms, encoding time = 1500ms.

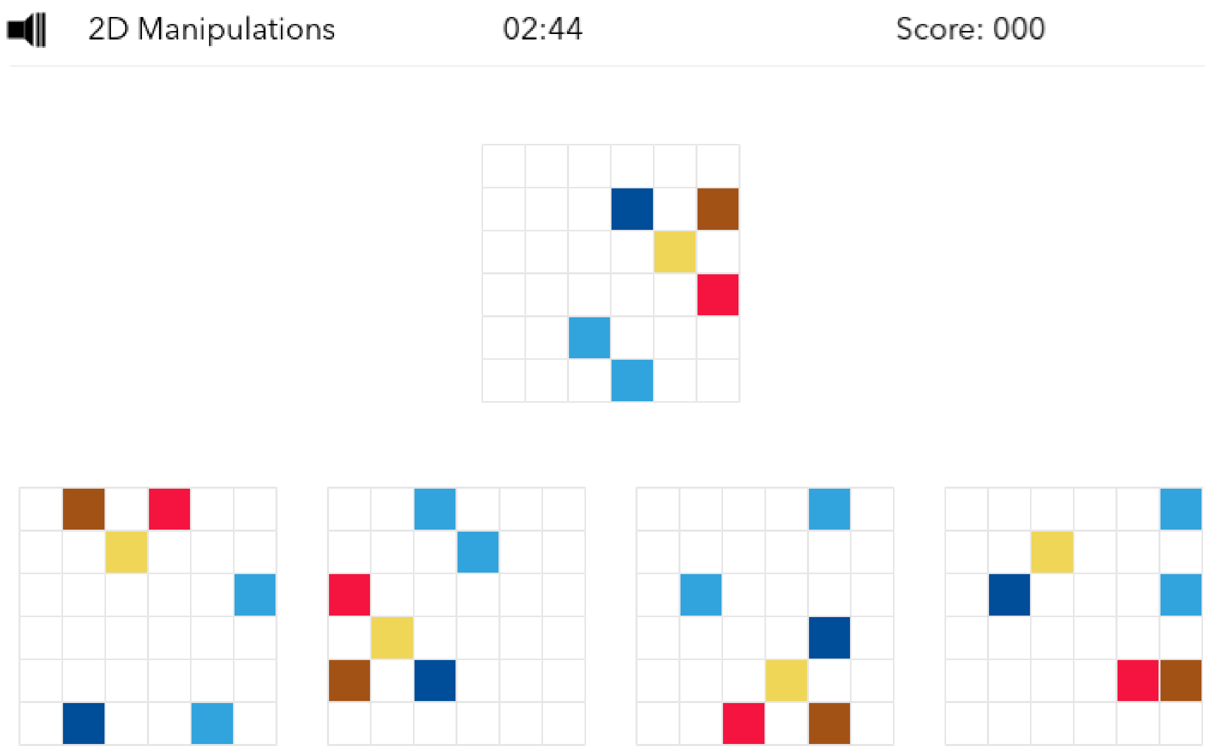


Target Detection
The target detection test measures spatial visual attention. The participant is presented with a target shape on the left of the screen and a probe area on the right side of the screen. After 3000ms, the probe area begins to fill with shapes, the participant must identify and click the target shape while ignoring the distractor shapes. Shapes are added every 1000ms and a subset of the shapes in the probe area are removed every 1000ms. The trial runs for a total of 120 addition/removal cycles. The target shape is included in the added shapes pseudo randomly, at a frequency of 12 in 20 cycles. The outcome measure is the total number of target shapes clicked.



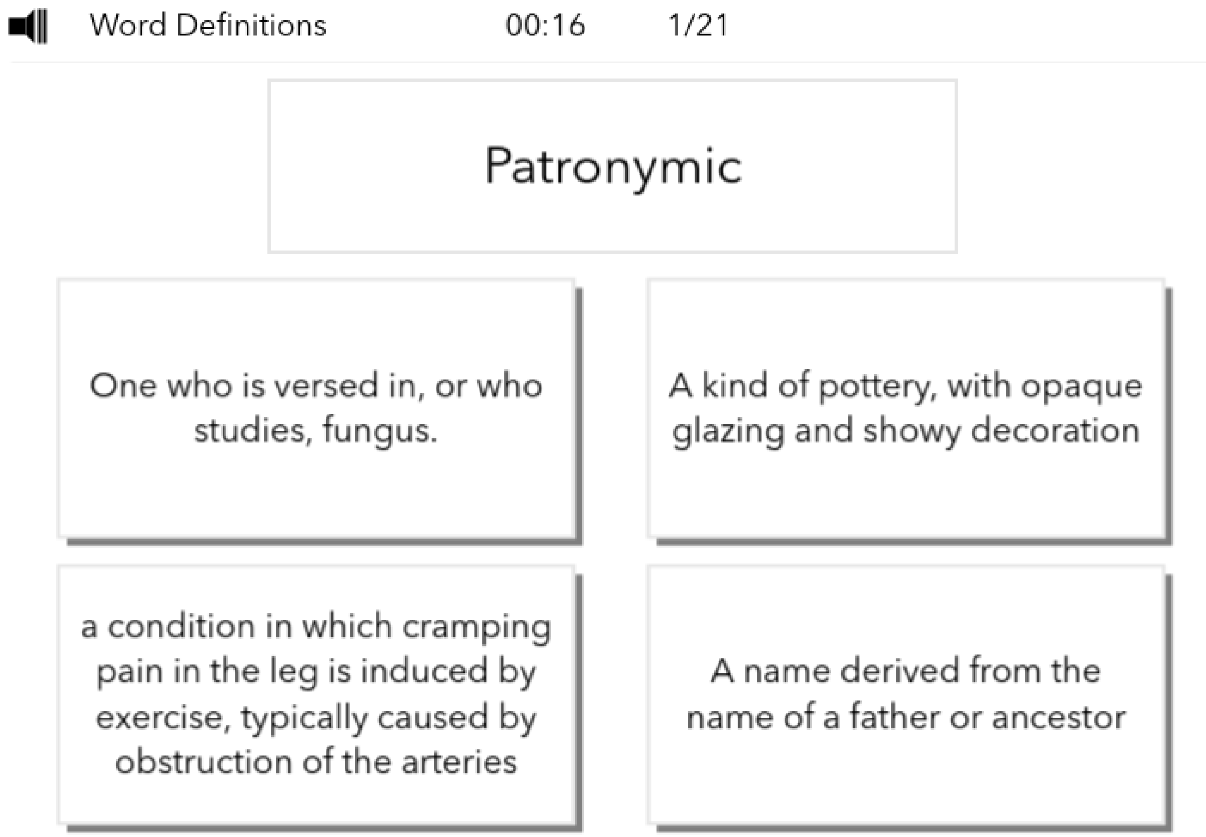
2D Mental Rotations

The 2D Mental rotation test measures the ability to spatially manipulate objects in mind (Silverman et al., 2000). In this version of the test, a grid with coloured squares is presented at the top of the screen, with a further four grids with coloured squares presented below (i.e. probe grids). One of the four grids is identical to the target grid above but is rotated by either 90, 180 or 270 degrees whilst the other grids differ by five squares. To obtain maximum points, the participant must indicate which of the four grids is identical to target, solving as many problems as possible within three minutes. For every correct response, the total score increases by one. The outcome measure is the total score.

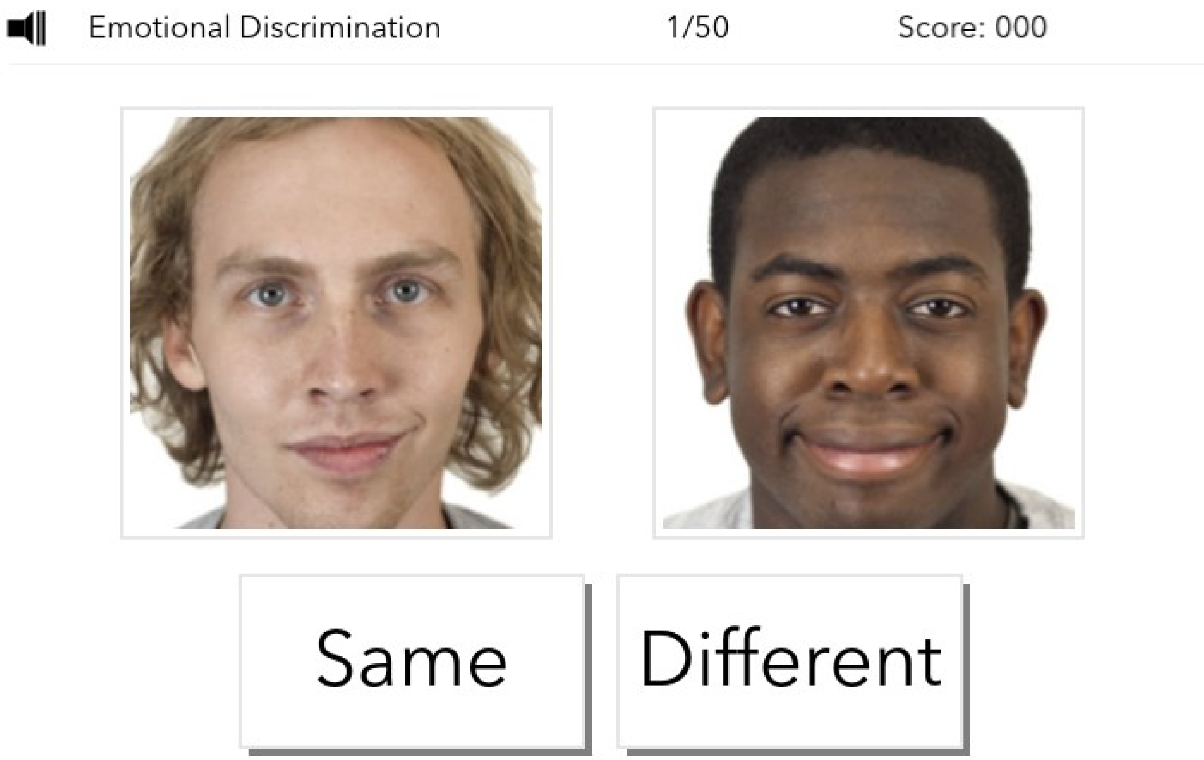


Analogical Reasoning
The Analogical Reasoning test measures semantic reasoning abilities. In this version of the test, participants are presented with two written relationships that they must decide have the same type of association or not (e.g. “Lion is to feline as cabbage is to vegetable”). Participants must indicate their decision by selecting the True or False buttons presented below the written analogies. Analogies are varied across semantic distance to modulate difficulty and associations types switch throughout the sequence of trials. To obtain maximum points, participants must solve as many problems as possible within three minutes. For every correct response, the total score increases by one. For every incorrect response, the total score decreases by one. The outcome measure is the total score.

Rare Word Definitions
In this test, individuals are assessed on their ability to identify the correct definitions of a words. Participants are presented with a word accompanied by four descriptive statements. They must decide which of the four statements provides the correct definition of the word. Words vary based on their frequency of use in English written language, resulting in rare and commonly used words to be presented. For each word, the participant has twenty seconds to choose a definition. To obtain maximum points, participants must answer 21 word-definitions correctly. For every correct response, the total score increases by one point. The outcome measure is the total score.



Face Emotional Discrimination
This test measures an individual's ability to identify and discern between emotions. Participants are presented with pictures of two people, each expressing a particular emotion (e.g. happy, neutral, angry, scared). They must decide if the emotions expressed by each person are the same or different. Trials vary based on the emotions used as well as whether individuals have congruent vs. incongruent emotional expressions. To obtain maximum points, participants must complete 50 trials as accurately as possible. For every correct answer, the total score increases by one point. The outcome measure is total score.


Emotional Discrimination
1/50
Score: 000
Same
Different

Chapter 5

Discussion

5.1. Summary of findings

In Chapter 1, I surveyed relevant literature mainly about the mechanisms of intentional learning from a behavioural and neural level. Based on the literature, I then developed a novel behavioural and a novel neural model that in evidence-driven manner. Further, I surveyed the relevant literature on the need for the "little" Big Five, the effects of psychiatric and neurological conditions on personality traits, and the associations between personality traits and learning respectively with an emphasize on theories and explained the aims and hypotheses of each subsequent chapters. This work provided a comprehensive survey of past literature, novel conceptual models, and hypotheses based on theories that can be empirically tested in later chapters and also future research.

In Chapter 2, I validated novel short forms of the Big Five personality inventory that could measure personality traits in a relatively short period of time and can be accompanied with other measurements. In addition, I found that the "little" Big Five is a valid measure and is very comparable to the full Big Five. Like full-version of the Big Five, they are also associated with demographic characteristics. By applying this "little" Big Five on people with psychiatric and neurological conditions, I also found that Openness and Neuroticism tend to be higher whereas Conscientiousness tends to be lower in participants with psychiatric and neurological conditions. Extraversion and Neuroticism did not show a clear pattern. This work provided evidence for a valid but yet short measure of personality that can be used for subsequent investigations regarding the associations between personality traits and intentional learning. In addition, this work contributed to a novel short form of the Big Five inventory that can be used in future studies. Finally, it also provides feasibilities for employing this scale in clinical populations such as people with psychiatric and neurological conditions.

In Chapter 3, I developed 9 intentional learning tasks across different types and complexities. I found a clear intentional learning effect as indicated by accuracy and RT. In addition, intentional learning performance can be explained by the type and complexity of learning. This study developed 9 novel intentional learning tasks at different complexity levels based on previous literature, which provided compelling but yet novel evidence regarding the construt validity of "what" and "how" in intentional learning. The internet-based learning tasks developed in this study can be used by researchers working in this area, and possibly can be included as part of neuropsychological battery that can be utilized by clinicians.

In Chapter 4, I assessed the multivariate associations between personality traits, cognitive performance, and different types of intentional learning (i.e., instruction-based, observational, and model-based) across three complexity levels (i.e., simple, complex, and model-based) using 9 novel intentional learning tasks I developed in Chapter 3. I found one significant mode in the relationship between personality and different intentional learning tasks and two significant modes in the associations between cognitive tasks and intentional learning tasks with different types across three complexity levels. Demographic characteristics may play a role in these associations. This study assessed the multivariate relationship between personality traits, cognitive performance, and different types of intentional learning at different complexity levels. It provides compelling support to the novel conceptual model I developed in Chapter 1. It also provides evidence regarding theorized associations between personality traits and intentional learning.

5.2. Interpretation

All of my work used big data approach, which has many advantages in cognitive psychology, including the ability to do finer grain analysis, complex modeling, and predictive modeling. Specifically, with a big data set, I can perform finer-grained analyses of cognitive processes. I can reveal patterns and individual differences that might not be apparent with smaller sample sizes, which enables accurate and comprehensive modeling of cognitive phenomena. Big data also enables me to construct more complex models that capture the multifaceted nature of cognitive processes such as the canonical correlation model. Finally, large datasets enable me to create predictive models that can forecast outcomes such as personality traits based on various factors such as demographics.

Different types of intentional learning at various complexity levels have been studied for a long time in the literature. My work in Chapter 1 provided a clear synthesis across past studies. Based on these pieces of empirical evidence, my theorical models proposed that intentional learning can be classified as instruction-based, observational, and reinforcement learning are they are sensitive to task complexity (i.e., simple, complex, and model-based). Results from Chapter 3 suggested clear learning effects across different types (i.e., instruction-based, observational, and reinforcement) and complexities (i.e., simple, complex, and model-based) of intentional learning as indicated by increased accuracy but yet decreased RT over time, which is consistent with the broad property of learning. In addition, these intentional learning tasks can be explained by types and complexities of intentional learning, which indicated that the intentional learning type and complexity are valid constructs in intentional learning research. Thus, these tasks can be used in future research given their validated psychometric properties. These studies contribute to constructs mentioned in the literature but are yet not fully supported by empirical data.

In addition, two models with one at cognitive level whereas the other at neural levels that account for intentional learning abilities have been developed in Chapter 1. These models posited the hypothesis that different types of intentional learning may have shared underlying basis, but they are still distinct in a way because different types of intentional learning may require various cognitive abilities and they do not recruit the same set of brain regions expect the multiple-demand (MD) system. Evidence from Chapter 4 indeed supported the notion that different cognitive abilities are required in intentional learning as I found two modes in the associations between cognitive performance and intentional learning, but their pattern is diverse, which provided support to the models I developed in Chapter 1. Moreover, the second mode provided partial support to the cognitive model by demonstrating that reasoning ability is particularly important in model-based learning.

In Chapter 1, I also found that personality is closely related to intentional learning as they share common brain networks. I started my investigation by validating the short version of the Big Five in Chapter 2 as it has long been suggested that long instruments could induce discouragement, fatigue, and inattention in the participants, especially making them hard to implement in clinical groups. This scale could avoid problems in inventories with huge number of items, which may impede the joint administration of multiple instruments and administration in people who have cognitive burdens for completing an inventory with a large number of items. The practical contribution of this study was that it provided a validated but short Big Five can be subsequently implemented when administrating with other surveys and to people who have burdens for completing the whole Big Five.

In addition, theories have been developed to account for why psychiatric and neurological conditions could affect personality traits. The results regarding personality traits are affected by psychiatric conditions provide some support to theories such as the predisposition/vulnerability model, the complication/scar model, and the spectrum model (Krueger & Tackett, 2003; Nigg, 2006; Tackett, 2006). However, since my study was cross-sectional, it would be impossible to confer if psychiatric disorders change personality traits (complication/scar model; Tackett, 2006; Whittle et al., 2006) or personality traits posit one at a higher risk of developing psychiatric disorders (predisposition/vulnerability model; Krueger & Tackett, 2003; Tackett, 2006). Similarly, the results regarding personality traits are affected by neurological conditions provide compelling support to theories regarding how personality traits may relate to neural substrates (DeYoung, 2010).

A significant canonical mode refers to a pair of canonical variates that exhibit a strong, meaningful, and statistically significant correlation between two sets of variables. In the contest of my study, there was one canonical mode existed in the association between personality traits and intentional learning and two conical modes in the relationship between cognitive performance and intentional learning, which indicates that there are one statistically significant correlation between personality traits and intentional learning and two patterns of statistically significant correlation between cognitive performance and intentional learning. However, the relationship between personality and intentional learning are small and diverse for different types (i.e., instruction-based, observational, and model-based) of intentional learning at three complexity levels (i.e., simple, complex, and model-based) and demographics may explain their associations, these results may indicate that personality or cognitive performance alone could not well taken intentional learning into account. Thus, intentional learning should be considered as a distinctive set of constructs.

5.3. Future research

My work regarding the application of the “little” Big Five was cross-sectional, the temporal order of personality and these diseases could not be established. For instance, theoretical models have proposed it may be the case that particular traits confer a greater risk for the development of a psychological disorder (predisposition/vulnerability model; Krueger & Tackett, 2003; Tackett, 2006) or development of psychological disorders alters an individual’s premorbid personality (complication/scar model; Tackett, 2006; Whittle et al., 2006).
In addition, people who score high in certain personality traits such as Neuroticism may be related to smoking (Kang, 2022a), which then contribute to a greater risk for the development of neurological diseases such as stroke (Shah & Cole, 2010). However, damages to the brain as a result of these neurological conditions such as stroke could also affect personality traits given that personality is closely related to the neural system according to Chapter 1 (De Young et al., 2010). Future studies should test if personality contributes to increased risks for certain conditions or if these conditions affect personality. Future research should also investigate how other psychiatric and neurological conditions that are not assessed in this study could affect personality traits as measured by the “little” Big Five.

Chapter 3 provided 9 psychometrically validated internet-based intentional learning tasks. It provided additional support to the type and complexity of intentional learning tasks that have been partially studied in the literature. It is important for future study to investigate the construct validity of these intentional learning tasks. These 9 tasks could be used in future research to look at how clinical conditions may affect different types of intentional learning (i.e., instruction-based, observational, and model-based) at various complexity levels (i.e., simple, complex, and model-based) given that intentional learning is a critical ability in daily life. As highlighted in

Chapter 1, learning from stimulation is a type of intentional but was not studied in my investigation, it is thus sensible for future research to compare the mechanisms of learning from mental simulation with other types of intentional learning that are studied here. Considering learning more broadly, there is also a need for future studies to compare and contrast different types of incidental learning. From a translational-clinical perspective, it is also sensible for future research to consider its feasibility to include these learning tasks as part of the neuropsychological battery that is currently given in patients. In addition, the sample size included in this research may be small. Applying these intentional learning tasks to a wider population may help it to determine if these tasks are effective and generalizable tools for capturing intentional learning abilities.

Chapter 4 found associations between personality traits, cognitive abilities, and different types of intentional learning. Yet, these associations did not appear to be consistent with hypotheses but may indicate that intentional learning should be regarded as a diverse set of constructs. Given this is a purely behavioral study, which makes the underlying mechanisms regarding why they are linked unclear given the neural model developed in Chapter 1. Future research needs to shed light on the underlying neural mechanisms of these associations. Further, I speculated that demographic characteristics may play a role in the associations between personality, cognitive performance, and intentional learning without directly testing these mediation effects. Future studies are needed to directly test whether demographics characteristics serve as significant mediators in these associations. Moreover, the associations between personality, cognitive performance, and intentional learning rates were rather week, future research may need to understand if other factors such as psychiatric (e.g., Di Simplicio et al., 2016) and neurological conditions may contribute to intentional learning ability.

Cross-sectional nature of this study makes it desirable for future studies to adapt a longitudinal approach to further clarify the causal relationships of these associations. Although evidence seemed to support the conceptual model I developed in Chapter 1 regarding the need of different cognitive abilities in intentional learning, but it is still possible that individual differences in intentional learning affect cognitive assessment tasks as almost all cognitive assessment tasks require learning from instruction and trail-and-error (i.e., reinforcement) but to varying degree. Future research could verify this by using tasks requiring involves less intentional learning.

It is also important for future research to consider if intentional learning is learned preferences or pre-determined traits. As shown, people who received more education tend to learn slower as they already have a good performance and the very beginning. Thus, intentional learning abilities can be possibly included by learned preferences (i.e., receiving more education). However, it is also possible that people who are better at intentional learning tend to receive mor education as they are good at it.

From a practical perspective, it might be interesting to study the relationship of intentional learning with one’s optimal role in the workplace as intentional learning is almost required in most types of jobs. As I showed, intentional learning is quite a diverse construct. Some employees might be good at learning from observation and trial-and-error whereas others can simply learn from reading instructions, which is more accessible and efficient because a lot of written instructions are available on the internet whereas learning from observation requires someone to teach and learning from trial-and-error is at the cost of making a lot of mistakes. Due to this, it is certainly possible that people who are good at instruction-based learning (IBL) can learn quickly and thus be promoted to a higher position in one organization. From a translational-clinical perspective, it would be valuable to include intentional learning tasks in the common cognitive batteries as these intentional learning tasks capture important abilities that people need in their daily life. However, doing so may need to consider factors in intentional learning as some clinical populations may not be able to perform such tasks (Parkin et al., 2021).

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